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PLATFORMS FOR BIG DATA BUSINESS MODELS IN THE HEALTHCARE CONTEXT

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﴿ اقْرَأْ بِاسْمِ رَبِّكَ الَّذِي خَلَقَ * خَلَقَ الْإِنْسَانَ مِنْ عَلَقٍ * اقْرَأْ وَرَبُّكَ الْأَكْرَمُ * الَّذِي عَلَّمَ بِالْقَلَمِ * عَلَّمَ الْإِنْسَانَ مَا لَمْ يَعْلَمْ ﴾

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UNIVERSITY OF OULU ABSTRACT OF THE MASTER'S THESIS
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0Abstract

The profitability of the business opportunity is defined by the level of owned data and its insights to the business organization. However, the existing literature has not identified how to link between different business models in the data-oriented systems. The previous research efforts focused on the technical aspects of data including data monetization, clustering, and data lifecycle. The purpose of this research is to understand how to link big data and business model thinking in the healthcare context. The main argument of this study provides a novel way to the modularity in the big data business models, which enables the system customers to control the system

Studies show if there is a kind of data-oriented platform that remind patients to do certain tasks (ex. nutrition and medicine reminders) before going to doctors and nurses; the patients would like to use it. In addition, around 90% of the platform users will recommend it to other patients and so on. This pushes the operators in the healthcare industry to transform their traditional human-based data systems into a computer-to-computer system. In the data-intensive systems like the healthcare industry, the value creation is done by monetizing data between system actors to analyze the data and develop extensive knowledge about the end customer. For example, the hospitals have the right to own and anonymize the patient data to ensure the privacy and security of patient information. Then hospitals monetize the patient data with their business partner who has the technical and analytical capability to analyze data. Later, they provide the system with useful insights gained from data analytics.

This is an exploratory phase of research where the qualitative case study approach is applied to examine the possibility of having a common platform for the integrated solutions in the data-oriented systems. To approach these platforms, an empirical study has been conducted over three case companies working in the healthcare context. The data were collected using semi-structured interview discussion. Similar qualitative approaches have been used in some prior studies to examine the value creation in the data-oriented systems and identify the future business models for the digital environments and IoT.

This research contributes to the existing literature by identifying four main platforms for big data business models. The modular platform is done due to the lack of knowledge about the end-customer, it grants system partners the right to control over their platforms. The partnership platform guarantees the continuity of the business process, the Ecosystemic platform gives the end customer the possibility to select what they need from the overall ecosystem. The ownership platform is related to the centralized control over the data source, enabling consistency of the business process.

Keywords

Big data, Business Models, Business Ecosystem, Modular Business, Healthcare context, Data Ownership, Data Monetization.

Additional information

This study is a part of the icory project that combines modern digital communication technologies, artificial intelligence, and robotics to take surgery care pathways to the next level.

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ABBREVIATIONS

3D	Three-Dimensional
AI	Artificial Intelligence
AIaaS	Artificial Intelligence as a Service
CF	Collaborative Filtering
E-commerce	Electronic Commerce
EDI	Electronic Data Interchange
EPR	Electronic Patient Records
IOS	Inter-Organizational Systems
IoT	Internet of Things
IPRs	Intellectual Property Rights
IT	Information Technology
OLAP	Online Analytical Processing
PCC	Performance-Oriented Congestion Control
SaaS	Software-As-A-Service
SAS	Statistical Analysis System
SMEs	Small and Medium Enterprises
SPSS	Statistical Package for Social Sciences

To the players in the healthcare industry, who provide solutions to make the patient lives easier!

1 INTRODUCTION

This thesis presents an explanatory framework for the big data business models in the healthcare context. In order to approach this framework, a combination of the common elements between big data and business models is done to identify the possible pathways of commercializing data-oriented platforms. This study is a part of the icory project, which aims to provide a framework for the business ecosystems and common platforms for integrated healthcare solutions. Accordingly, this chapter presents the background of the research, research scope and objective, research method, key concepts, and structure of the research.

1.1 Background of the research

Today's revolution in the healthcare industry as one of the world's largest growing industries; is shifting the system from a fee-based model into a value creation model (Nambiar et al, 2013). These shifts lead business organizations to seek more knowledge about their end customers, expand their business scope to include a wide range of products/services, and establish multichannel business relations with other business partners (Weill & Woerner, 2015). However, when it comes to human lives; the profit should not be the primary motivator for healthcare organizations. Accordingly, the speed in the transmission of information and advancement in the analytical techniques provide pathways for healthcare organizations to shift towards value creation models (Khaloufi et al, 2018). Enabling healthcare system to go further and expand their scope to not only include the concept of saving human lives; but also, to improve the system quality and provide a value-based system for its users "patients" (Raghupathi & Raghupathi, 2014).

The Finnish movement towards digitalization and rapid development in the technology research and Tech industry are enhancing the increased use of data-oriented systems. Further, the Finnish healthcare system is evolving towards user-centric "patient" information system (Pitkänen & Pitkäranta, 2016). On the global scale, the development of the healthcare system and the availability of different caring options substituted the paper recording system with integrated data-driven systems. These systems have the ability to collect, store and analyze the overwhelming amounts of patient-generated data (Raghupathi & Raghupathi, 2014). The Electronic Patient Record system (EPR) is a digitalized information system that collects clinical and administrative data in one place. Yet, the healthcare system is an intensive data-driven system, it generates billions of data worldwide (Tempini, 2017). These large volumes of data represent challenges for some healthcare organizations. Mainly from the perspectives of data ownership and data monetization. These challenges are related to the loss of control over the whole business process “decentralization”. On the other hand, it enables organizations to get rid of the traditional structure and grow vertically; opening the pathways for having an interdependent network of business actors; to coordinate their capabilities and deliver values to their customer (Van et al., 1995; Grossman & Hart, 1986).

Since humans are different and they do not probably understand everything in the same way. Each human has had different mental capabilities that process the information based on own understanding and the influence for the external environment. (Osterwalder et al, 2005) argue, it is necessary to have a simplified generic tool to explain the overall concept of the business. At the meantime, it will be able to provide a common language between industry stakeholders to ensure that everyone understands the business concept and the relationship between its elements. From this perspective, the business models are enabling the shift from the traditional management approaches, introducing innovative ways of deploying company resources, and ultimately capturing and creating the unique values for the business itself and its customers (Demil et al, 2018).

Back to Porter (1979) who suggested a model for analyzing the organizational capacities and capabilities. Further, he identified the context of businesses within a dynamic environment of suppliers, customer, and competitors. Each element of this environment has a bargaining power that needs to be considered while formulating the business strategy. Nowadays, business organizations are required to operate within an ecosystemic environment. It opens the ways to establish concrete competitive advance, establish a rewarding corporation, and quickly respond to market competition (Ahokangas et al, 2010). Yet, the research around the ecosystemic concept is existing. The need for identifying new frameworks for business models in the ecosystemic context “from sharing perspective” is the main motivation for this research. Because business organizations are always in need to remain competitive. Accordingly, they either require a continuous development to their current business model or adopting new platforms of business models (Wirtz et al, 2010).

The ecosystem business context has been defined by Iivari et al. (2016) as a complex network of interdependent business organizations involved in the business process. It operates as a platform for value creation and capture. Further, the ecosystemic business context is considered as an enabler for business organizations to acquire the extensive knowledge about the end customer (Wirtz et al, 2010), that is done by establishing linkages between internal business functions and external trade partners. It enables the whole ecosystem to gather all available possible information about customers; aiming that customers will get the best experience (Weill & Woerner, 2015). Besides, the ecosystem business context in the data-oriented systems is defined as an enabler for information accessibility through multiple platforms like SaaS, AIaaS and other similar platforms. These platforms enhance the speed of information transfer and grant system users a cost-efficient accessibility option (Picot, 2015; Ma, 2007; Ju et al, 2010).

The existing literature has not proved yet how different business models can be aligned to work together in the data-oriented systems; especially when it comes to the healthcare context as a data-driven system (Raghupathi & Raghupathi, 2014; Tempini, 2017; Gomes et al, 2018). Also, there is not enough research found on how to link the big data with the business model thinking, as the previous research efforts focused on the technical aspects of data related to data monetization, clustering, and data lifecycle. The priority has been given to improve the data system without minding customers and business requirements (Khaloufi et al, 2018). Yet, the research is needed to understand the ecosystemic business model from the notion of value capture and creation in the data system, that may open the pathways for new innovations in the healthcare sector (Gomes et al, 2018). Further, the aspects of big data and digitalizing should be examined from various perspective including the business practices, value creation, and customer choice (Tempini, 2017). Consequently, this study aims to increase the understanding of the value capture and creation from the ecosystemic perspective. Further, it aims to fulfill the existing research gap and develop platforms for big data business models in the healthcare context, by combining the common elements of the big data-oriented systems and ecosystemic business models as a tool for value creation and delivery.

This study contributes to the existing literature of the business models in the digitalized environment (Weill & Woerner, 2015; Wirtz et al, 2010) by identifying the platforms for big data business models in the healthcare context. It identifies the main aspects of the data-oriented models from several aspects including the ownership of data, the integration of the systems, the partnership and modularity of the platforms. Usually, the data-oriented systems are categorized by the centralized control over the data platform, which collects and process data (Grossman & Hart, 1985). The findings of this study suggest that; the system should be based on grating standardized access for the platform users (ex. hospitals) and maintain centralized control over the whole platform. In addition, this study complements the findings of Weill and Woerner (2015) about the types of business models in the digital setting; the findings suggest modular platform for data business models in the healthcare context. The modular platform is enhanced due to the lack of knowledge about the end customer, that the platform owners have. Based on the concepts related to customer-centricity and value creation, the cooperation between platform owners and data-owners' "hospitals" is a key success element for these platforms. Because hospitals collect and anonymize patient data, and then collect usability feedback from the patient. In return, the partial control over the platform should be granted to hospitals to enable the optimization of the platform accordingly.

Further, the interdependency between ecosystem actors should contribute to the consistency and efficiency of the business process. It validates the findings of Wirtz et al, (2010) of developing the ecosystem to overcome the rivalry power and maintain the competitive advantage. From the big data perspective, the ecosystem is composed of multiple actors who co-operate to provide their customers with the data-oriented platform. The ecosystem needs to be built on the basis of customer selection; it should not be built around the meeting the requirements of the revenue model of each actor in the ecosystem. Otherwise, the overall price will be extremely high for the end customer. Actors in the ecosystem need to provide a wide range of features over their data-oriented platforms, keeping the opportunity for the customer to select what they want from the whole ecosystem. But it remains unclear how different companies can align different revenue models together to create and deliver values for the customers.

1.2 Research scope and objective

The big data is transforming the traditional ways of doing nowadays businesses. The massive amounts of data require specific technical and analytical capacities to process the data and gain useful insights out of it (Najjar & Kettinger, 2013). In the data-oriented businesses like the healthcare industry, the massive amount of patient data generated over time needs smart systems to be collected, analyzed and processed (Raghupathi & Raghupathi, 2014). Hence, business organizations need to operate within an ecosystem of several actors to enable the speed in information transfer between system actors (Iivari et al, 2016; Loebbecke & Picot, 2015). A certain level of integration between system actors is needed; especially in the data-oriented systems where the aggregation around one major sharing center is needed (Demil et al, 2018; Ju et al, 2010; Ritter & Schanz, 2018).

Earlier studies identified the patterns of integration in the ecosystemic business models have been identified in terms of value creation and innovation of business process, as the ecosystem help all partners to get complement their business process and gain the extensive knowledge about the end customer (Iivari et al, 2016; Gomes et al, 2017; Wirtz et al, 2010; Weill & Woerner, 2015). But neither of these studies have proved yet the notion of control in the data-oriented ecosystems, as the data owner (ex. Hospitals) have the bargaining power over the owned data, while the business organizations own the system for analyzing this data (Khaloufi et al, 2018). Accordingly, a certain level of modularity in the big data system needs to be identified, in terms of controlling the data platform and optimizing its content. Yet, Weill and Woerner (2015) examined the modularity of business models, mainly from the notion of creating a modular system to enable business organizations to know more about their end customers. But in the healthcare system as a data-oriented system, the platform operators provide hospitals with data-oriented solutions. These platforms are used by end users (patients). Accordingly, a certain level of modularity is needed to enable hospitals to identify patients needs, then optimize the platform accordingly. But Weill and Woerner (2015) have not identified the aspects of modularity in the ecosystemic business model.

On the other hand, the research trials of Van et al. (1995) and Grossman and Hart (1986) examined the technical aspects of the data related to the centralized control over the data system. This right grants the planning and control of database to one central business organization and distributes the access to the platform users. However, this does not meet the requirements of value creation, which requires all actors in the ecosystem to have extensive knowledge about the end customer (Weill & Woerner, 2015). In the healthcare system, hospitals have the main touchpoint with patients (system users) not the platform operators. As the get access to patients through hospitals, so a certain degree of platform optimization and modularity is needed to provide a user-friendly platform based on the findings of Weill and Woerner (2015) of the modular business model, that allow companies to know more about their end customers.

Therefore, this study aims to fulfill the identified gap in the literature especially in the modularity of data-oriented platforms as an ecosystemic process and identify the pathways of value creation in the data-platforms. Further, it has not proven yet how to align different business models to work together in the big data and AI era (Gomes et al, 2018; Tempini, 2017). This research is conducted to develop a framework for understanding the big data business models in the healthcare context, which can help healthcare organizations and managers to better understand the notion of business models and modularity in the big data context and its influences on the healthcare system. Further, the study examines the various types of data existing in the healthcare context. To accomplish the research objective, a research question has been identified to reflect the overall scope of this study as follows:

How to link big data and business model thinking in the healthcare context?

This question aims to guide the study in identifying the links between big data and business model. The question is specific to the big data and aspects related to the data sharing and control over the data platforms. In addition, identifying the business models applicable for the data-oriented systems since it is exploratory research, that aims to identify on the generic level the suitable business model for the big data in the healthcare context. The answer to this research question aims to contribute to the theoretical and managerial levels. As the aim of this study to help data-oriented systems to create values and improve the usability of the big data platforms by getting extensive knowledge about the end customers.

1.3 Research method

The qualitative case study approach was adopted in this exploratory phase of research to collect and analyze the empirical research data. Indeed, the qualitative research approach is used to identify a certain phenomenon that does not have any clear outcomes yet (Yin, 2003). Further, it enables researchers to gain a deep understanding of the research phenomenon and examine the various aspect of this phenomenon from the viewpoints of the participants (Chesebro & Borisoff, 2007). The results of qualitative research should be able to be replicated by other researchers using the same research approach (Leung, 2015).

The replicability of the qualitative research refers to the consistency of the research process, that means if other researchers used the same approach; they will be able to reach the same results over time. Whilst the validity of qualitative research relates to the appropriateness of the tools used to conduct the empirical study (Golafshani, 2003). In this research, the case study approach was applied to the researcher the possibility to gain a deep understanding of the research topic. The research is built around three case companies working in the healthcare context, and the data is collected using the semi-structured interview methodology.

The research methodology, data collection, and analysis method are discussed in detail in chapter 3. Figure1 provides a roadmap for this study to find suitable ways of linking the big data with business model thinking in the healthcare context. First, the theoretical background of this research is formulated to conclude a preliminary answer to the research question. Then, provide a guideline for the empirical study part. As mentioned earlier, the aim of this research is to identify a framework for data business models in the healthcare context. To approach this goal, the researcher identified the lack in literature connecting the big data with the business model thinking. Accordingly, the literature background of this study is divided into three parts:

The first part defines the concept of big data as large volumes of datasets, that has transformed the decision-making process from a centralized one into a full integration between internal system capabilities and external actors in the business network. Further, the discussion continues to include the characteristics of big data like including data monetization, data ownership and centralized control over the data system, and Electronic Data Interchange (EDI). Then examining how the big data is transforming the healthcare system as a data-driven system. Besides, the big data analytics in the healthcare system, and how value is created and delivered in the data-oriented systems like the healthcare industry.

The second part provides an overall view of the business models concept; including a discussion about the transformation of the business model thinking and new forms for business models in the digitalized environment. Nowadays business models can be content-oriented, commerce-oriented, context-oriented, or connection-oriented. Further, the discussion continues to include how to create values for customers either by adapting the ecosystemic business context, the multi-channel model, or the modular platforms. Indeed, the discussion is focused on the notion of value creation and benefits to the healthcare industry.

The third part compiles the common elements between the previous parts two parts "big data and business models". Then synthesizes the literature background and suggests a new framework for guiding the researcher in the empirical study part to identify the platform for big data business models in the healthcare context; based on the common elements between big data and business models. Afterward, a qualitative case study research approach is adapted to approach this framework, the research approach is discussed in chapter 3.

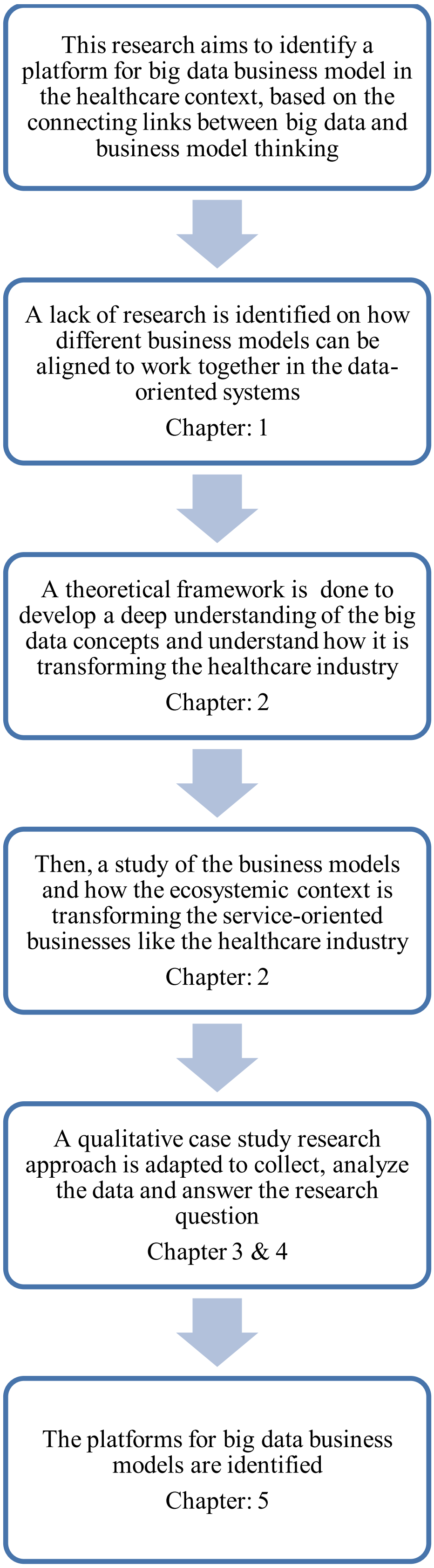

Figure 1. Research roadmap

1.4 Key concepts

This study identifies four major key concepts as follows:

1st. Big data

The large volumes of data that include terabytes and petabytes of data. It cannot be stored nor analyzed by the basic analytical techniques, it is done through smart systems which are known as a computer-to-computer system (Jeble et al, 2018; Fan et al, 2014; Raghupathi & Kesh, 2007). According to Russom (2011), big data has three main attributes: volume which refers to the overwhelming amounts of generated data over time, the velocity which means speed by which the data is generated and processed. The variety of big data refers to the various forms of data like images, audios, texts, numbers, and other forms. The concept of big data transformed the business process from a static operation into a dynamic network of interacting business organizations, that provide reliable inputs for the value creation and well-informed decision-making processes (De Mauro et al, 2016; McAfee et al, 2012).

2nd. Big data in healthcare

Raghupathi and Raghupathi (2014, p.1) the sets of the electronic healthcare generated data that is so large and complex to manage by the normal data tools. It requires specialized software and or/hardware to manage and analyze the data. Ex. Electronic Patient Records (EPR) which collect and store patient records in a digital format. From this aspect, the platform operators in the healthcare system are not interested in the patient data itself, but they are interested in the insights they might get from this data. Accordingly, the quality of healthcare generated data is the responsibility of healthcare operators like hospitals, clinics, and medical centers. As they have the responsibility of collecting, anonymizing, and transferring patient data to the platform operators (Jee et al, 2013). The platform operator provides healthcare system with solutions to analyze patient data, and then provide doctors and nurses with useful insights concerning the patient status and the possible treatment options (Jeble et al, 2018).

3rd. Business models

Osterwalder et al. (2005) business model is a planning tool that aims to coordinate between organization internal and external functions to covert the available resources into capabilities, and then create and deliver the value. According to Ahokangas et al. (2014, p.265) business model is an architectural tool which enables the easy visualization of organization capabilities, decisions, and competitive advantage. The business model "as a tool for value creation and capture" contains nine elements: value proposition, customer segments, channels, customer relationships, key activities, key resources, key partners, cost structure and revenue streams.

4th. Ecosystemic business

A network of complex interacting organizations and individuals involved in the business process (Moore, 1993). All actors involved in the ecosystemic setting share their resources and capabilities to enhance the business process and open the pathways for new innovations. In addition, the ecosystem business involves external organizations like universities driven spinoffs and research activities that provide support for the business process. It may also include external industry partners, associations, and non-commercial stakeholders. The ecosystemic business is characterized by complexity and interdependence between all partner organizations (Iivari et al., 2016; Gomes et al, 2017). Companies get involved in the ecosystemic context to gain comprehensive knowledge about their end customers and ensure the delivery of great customer experience (Weill & Woerner, 2015).

1.5 Structure of the research

In order to accomplish the aim of this study, the structure of this study is divided into three major phases: The theoretical background phase, the research design and empirical study phase, and the findings and conclusion phase.

In chapter 2, the literature background discusses the major key concepts of this study. The key concepts are divided into four main sub-chapters. The first sub-chapter defines the big data and provides a comprehensive framework for its characteristic including data monetization and the pathways of monetization. Then, the discussion flows around data ownership and data sharing concepts. The discussion includes the challenges and benefits for the business organization ranging from the decentralization in organization power until the possible partnership with other business organizations. The second dub-chapter defines the big data in the healthcare system and provides a conceptual framework for the importance of big data in the healthcare system, the big data lifecycle in the healthcare system, the analytics of big data in the healthcare system, and then identifies the driven benefits for the healthcare system. The third subchapter discusses the business models in various settings and ecosystemic businesses. The subsequent chapter provides a synthesis for the literature review phase and suggests the framework for platform-based business models.

The research design and qualitative case study approach are discussed in chapter 3; outlining the basis by which the researcher used to select the qualitative case study approach for this exploratory phase of research. Further, the chapter discusses the data collection process "semi-structured interviews. Appendix I" and the analysis method. The empirical data is analyzed in chapter 4 with regard to the theoretical framework of this study. Finally, in chapter 5; the answer for the research question is discussed and the platform for big data business model in the healthcare context is defined. Further, the theoretical contributions, limitations, and evaluation of the study, managerial implications, and recommendations for future research are discussed in this chapter.

2 LITERATURE BACKGROUND

2.1 Big data

Throughout the recent decades, the concept of data has developed from being only limited to the textual forms to bring up new forms of data including; images, videos, voices, texts, and log files (Jeble et al, 2018; Davenport and Dyche, 2013). Big data is a large volume of datasets that are accumulated over time and it becomes available through the digitalized systems (Constantiou & Kallinikos, 2015). This chapter discusses the evolution and shifts in the data system, the definition of big data, the collaborative recommendations in big data, data monetization and the pathways to monetize data, data ownership, data sharing, and electronic data interchange, and the driven benefits to the business organization.

2.1.1 Evolution and definition of big data

Thinking about the era of Pharaohs in Egypt and the world's oldest civilization, we will find the documentation of every element is the key to keep the mysteries and memories of their civilization until today. Pharaohs used to physically document everything through the hieroglyphic languages on the walls of temples and tombs, they used texts to describe the art of mummification, laws, and social rules and relations. Keeping sincere evidence for humans about the importance of data and documentation (Wenke, 1991). However, we are living in the 21st century not at Pharaohs era anymore. Thanks to the advancement in information technology, human civilization is moving from the physical documentation to the digital system (Khondoker, 2018). The shift toward digitalization accelerated the accumulation of data because of the speed in information transfer and accessibility to the internet and many other technological innovations (Kitchin, 2014). It raised up the need for using more sophisticated techniques to record and analyze the aggregated volumes of data (Jeble et al., 2018) because the traditional recording methods are not effective anymore. This transformation is known as the epoch of big data (Khondoker, 2018; O'Leary, 2013).

The increasing volume of data has transformed nowadays business practices (McAfee et al., 2012; Bharadwaj et al., 2013; Jeble et al., 2018). In terms of defining new business strategies to deal with digital technologies, expanding business networks and collaborating to build an interconnected relationship business models, and then figuring out new insights for the value creation strategy (Bharadwaj et al., 2013). In the meantime, humans ability to develop new systems that are able to manage and analyze multiplexing data from several and complex sources is growing over time (Keim et al, 2006; Cook & Thomas, 2005). Earlier, business organizations used to face some challenges while collecting and analyzing the overwhelming amount of data (McAfee et al., 2012). Regardless of the importance of data usage in proclaiming the year-ended reports and predicting the forthcoming year trends (Walker, 2014). This tremendous amount of data represented some challenges for the business organizations either in overcoming or sustaining a well-balanced competitive situation among their rivals (McAfee et al., 2012).

The concept of big data has changed the traditional view of the business practices over the last two decades, it brought up the concept of business intelligence based on big data analytics. In the late 1990s, the term of big data used to describe the enormous amount of data, that cannot be analyzed by simple techniques and it needs more complex analytical methods (Chen et al, 2012; Davenport 2006). The concept of big data became increasingly important for the business and research community, opening the pathways for new research trends related to data analytics and business intelligence (Chen et al. 2012). In large companies, the big data and its analysis cannot be separated from the company structure and it should be integrated with all functions across the organization (Davenport and Dyche, 2013).

Definition of big data

According to Ramamurthy and Premkumar (1995, p 332), "70*% of day-to-day business data traditionally entered to computers, are manually re-entered into another, and that about 25% of the total cost of transactions comes from data entry and re-entry. Indeed, it is a waste of corporate resources"*. From this perspective, the concept of data has evolved over the last two decades from a traditional day-to-day transaction recording system into an interactive system between information technology, cloud computing, mobile devices, and the internet of things (IoT) (Jeble et al, 2018). The transformation provided a profound for a new research opportunity either on the academic side or the business side (Kitchin, 2014). And it resulted in producing an interconnected-complex set of data, that is known as the big data (Jeble et al, 2018; Kitchin, 2014). Big data is connected with the development in the field of information technology, that have produced a wide range of data reliant applications (Jeble et al, 2018). Indeed, these applications have transformed the process of decision making from a static process into a dynamic interaction between internal functions and external nodes that represent all actors involved in the business networks (De Mauro et al, 2016; McAfee et al, 2012).

Big data consists of an immense volume of data (Jeble et al, 2018; Fan et al, 2014; Kitchin, 2014). Referring to terabytes and petabytes of data (Shirkhorshidi et al, 2014), which is complex to be processed using standard facilities like Excel sheets nor stored in a single storage device (Kitchin, 2014; Strom, 2012). Big data refers to the massive amount of digital information generated over time, which represents a reliable source of information for the decision-making process (Khondoker, 2018; O'Leary, 2013). From the technical side, the big data means Hadoop which Hadoop is open source software, that is designed for the distributed processing of large data sets across clusters of computers using simple programming models (Raghupathi & Raghupathi, 2014; Jeble et al, 2018)

Russom (2011) big data cannot only defined by the volume of data. The main three attributes of big data (volume, velocity, and variety), which is referred as the three V's of big data (Figure 2) (Khaloufi et al., 2018; Russom, 2011; Raghupathi & Raghupathi, 2014). The volume refers to the terabytes or petabytes amounts of generated information, the velocity refers to the speed of data generation and processing, and the variety relates to the data types: structured, semi-structured, and unstructured data. It includes various forms like images, audios, texts, numbers, and other forms.

Kitchin (2014) big data is formed in sets of several data, that include structured, semi-structured, and unstructured data. According to Raghupathi and Raghupathi (2014), the structured data is the data generated by normal or machine “automated” recording and it can be handled easily. In terms of storage, analysis, and recalling. Abiteboul (1997, p.2), defined the semi-structured data as "the data that is neither raw data nor very strictly typed as in conventional database systems". Feldman and Sanger (2007, p.57) the unstructured data is the data that does not have the recognizable structure/category. The analytics of unstructured data are extensively used in the business practices to formulate structured dataset sources and elaborate the efforts for the decision-making process.

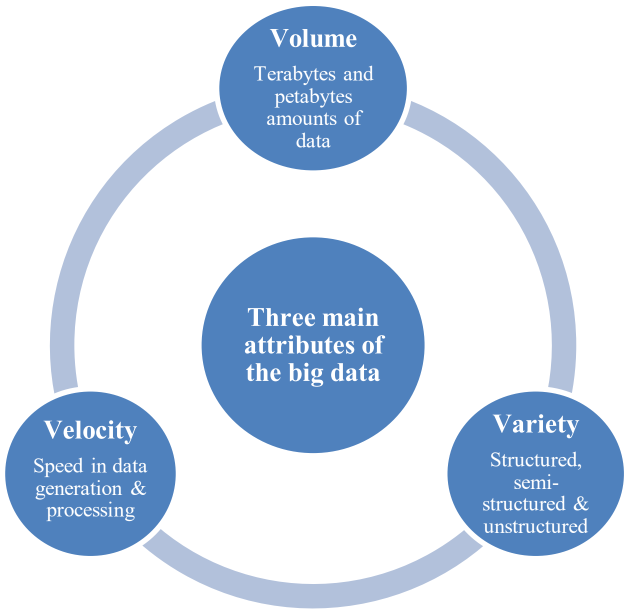

Figure 2. The attributes of big data. Adapted from Russom, 2011; Khaloufi et al., 2018; Raghupathi & Raghupathi, 2014)

Early in the 21st century, the term of big data described systematic huge volumes of data, generated on a continuous basis, seeking flexibility and direction towards specific scope (Jeble et al, 2018; Kitchin, 2014). Indeed, the big data brought up new forms of data including; images, videos, voices, texts, and log files (Jeble et al, 2018; Davenport and Dyche, 2013). This new forms of data can be analyzed using various technologies to enhance the decision-making process, and then introduce efficient strategies for cutting down the operating costs (Jeble et al, 2018). Thanks to the cluster algorithms run by Hadoop and similar tools, data storage cost has cut down to the minimums (Davenport and Dyche, 2013).

Collaborative recommendations in big data

Today, the profitability of business opportunities can be defined by the levels of owned data and its analyses in several organizations (Chen et al., 2012). For example, taking LinkedIn as a pioneering professional network which includes more than two hundred million users. Besides the massive amount of data provided by its users, LinkedIn uses collaborative filtering technology to provide suggestions for the best matching networks between users, jobs, and companies. Moreover, collaborative filtering technique helps LinkedIn to predict the interests of users based on the search history, connections between users on other social networks (Like Facebook, Twitter, etc.), and previous job titles or the educational field (Sumbaly et al, 2013; Reda et al, 2012). The Collaborative Filtering (CF) approach is a data-driven feature, known as a recommendation system. In the e-commerce websites and other electronic-based platforms like Netflix; CF provides behaviorally targeted recommendations. It assists users to compare between similar items and easily make their choice among the overwhelming amount of options (Koren & Bell, 2015 p. 77 - 80).

In the case of e-commerce websites like Amazon, eBay, or AliExpress. The CF system uses users behavior as an explicit input data to generate predictions based on the matching between users interests and the offering. These predictions are formed based on user browsing history, frequently viewed pages, user feedback, and ranking. According to Ma et al. (2007), the CF system uses two popular approaches to analyze the available data. In the memory-based approach, the system uses Performance-Oriented Congestion Control algorisms (PCC) to predict the user preferences based on the similar information provided by active users.

The Model-based approach uses cluster modeling to build hierarchal expectations of customer prediction. It is used when there is a scarce of the available data. However, it is not the optimal technique for the CF system. Because it takes a long time to build hierarchal consistency when there is not enough data available about customer expectations. In addition, the level of accuracy is not high like the PPC algorithms (Ma et al, 2007; Resnick et al, 1994; Xue et al, 2005).

2.1.2 Data Monetization

As discussed in the previous chapter about the driven benefits of applying the big data concept in healthcare; the process of predicting customers needs will be more accurate, the connection with stakeholders will be improved, the processes of detecting frauds if they happen will be more efficient, and the overall benefits to the system users “patients” can be represented in an early diagnoses, (Raghupathi, 2016). From this perspective, the development in information technology and speed in data transfer in recent years are reshaping the nature of business practices within the digital context (Iacovou et al., 1995).

The big data open the pathways for having new intangible assets that strengthen the competitive situation of the organization by adding new innovative ideas to the business offering (Constantiou & Kallinikos, 2015). Taking healthcare as an example, data-based smart devices that track human vital signs, and then generate data that enables the care system to track the before and post-treatment patient status. This will enable the early diagnoses and speed up the treatment process. In addition, it will help healthcare providers to minimize the waiting times.

Hence the big data is transforming businesses into the digital environment which brings new challenges to the current businesses practices. Therefore, it is necessary to understand the ways by which the information is collected, aggregated, and then analyzed (Woerner & Wixom, 2015). Afterward, the generated information will be ready for use, sharing, or selling. Thus, the concept of data monetization arises which requires the business organization to have the technical capabilities in forms of business infrastructure system including software, hardware, and business networks with other business operators to aggregate and analyze data. In addition to the human capabilities in form of professionalism and analytical capacity of company employees, suppliers/partners; to plan and strategize the way by which the company will monetize its data (Woerner & Wixom, 2015; Najjar & Kettinger, 2013). Ultimately, the monetization of data will provide companies with the opportunity of improving customer experience, generating more leads in relation to the sales part, and evenly being sold to other business entities (Perler, 2013).

Pathways to data monetization

Najjar and Kettinger (2013, pp 213-214) defined the data monetization as *"when the intangible value of data is converted into real value, usually by selling it. Data may also be monetized by converting it into other tangible benefits (e.g., supplier funded advertising and discounts), or by avoiding costs (e.g., IT costs)".* Data monetization helps the company to identify the strategic ways to make the best use of the available data, and then improving the business process and company relationships with customers and channel partners. The Monetization provides the company with rivalry power in terms of data accuracy and reliability (Perler, 2013). Furthermore, Najjar and Kettinger (2013, pp. 215 - 216) defined three pathways for data monetization (Figure 3).

Move directly to higher risk and higher reward: as a direct risky way of monetizing the data, it requires the company to develop the analytical and technical capability at the same time. Iacovou et al. (1995), the company needs to have adequate financial resources to invest in the technical infrastructure and provide humans with the capability to use these systems. However, Najjar and Kettinger (2013) argue, the investment cost is relatively high, which is necessary for the company to train its employees and trading partners to acquire the skills needed to deal with the follow of data between business organizations.

Build analytical capability first: the second pathway requires the company to directly invest in the internal analytical capacity, which is represented by the manpower. Following this pathway, the company needs to offer apprenticeship programs for its employees or hire professional analysts. Afterward, the company can invest in the technical infrastructure to speed up the process of data monetization and expand the analytical capacity.

Build technical data infrastructure first: the business organization needs to invest in the technical infrastructure to acquire the necessary analytical capability. Thus, establishing the company's own system or outsourcing the system is the available strategic option in this pathway. However, if the set cost is relatively high, the company can leverage its supplier/channel partners technical capability to get a quicker pathway to monetize its data through the business channels and reduce its costs. O'callaghan et al. (1992), the data sharing is a cost-efficient approach, that gives SMEs the abilities to take the initiative towards applying monetization techniques to its data system.

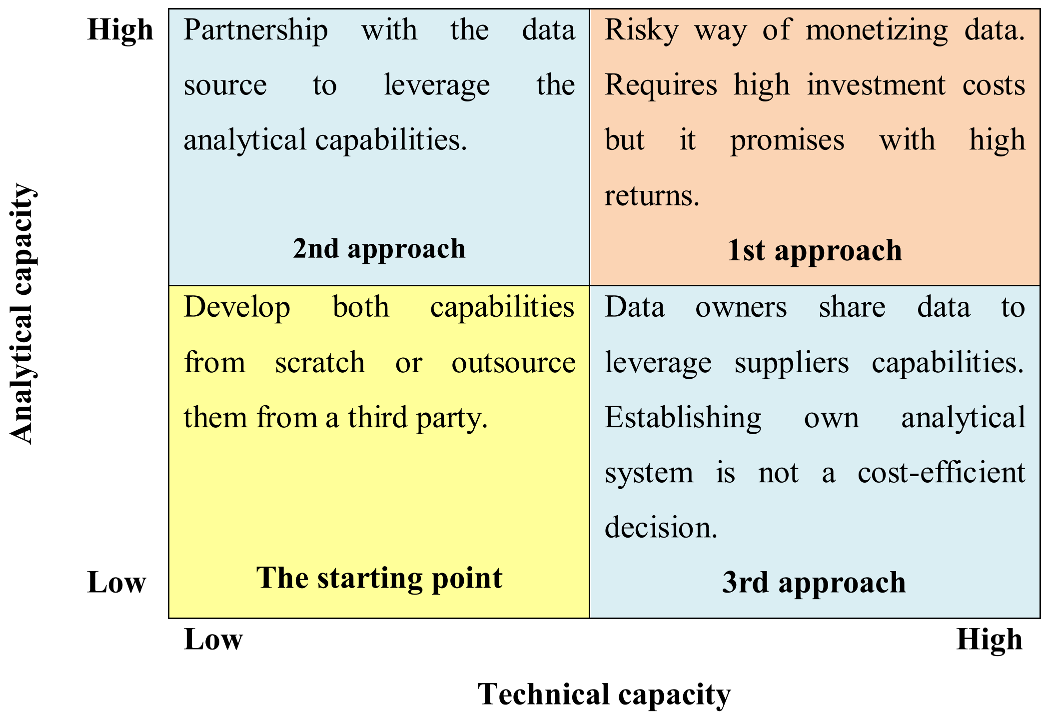

Figure 3. Data Monetization. Adapted from Najjar and Kettinger (2013)

2.1.3 Data ownership and Electronic Data Interchange (EDI)

The monetization makes the data accessible across different business channels. In the meantime, the intangible characteristic of data "ownership" can impact organizational control and effect the centralization of business influence in a certain area. Grossman and Hart (1986, p.716) defined the ownership as *"the company's effort to obtain/purchase the residual right of control"*. According to Van et al. (1995), data ownership is defined as one of the main elements for the success of the information-based systems. The ownership of data requires the centralization of information in one single database to ensure the control over data and maintain the level of data quality. The self-interest in data ownership helps data owners to sustain the quality of data because owners will have a greater interest in data than the nonowners. In addition, the ownership generates a motivated behavior towards the value maximization (Hart & Moore, 1990).

Van et al. (1995) suggested a framework for describing the architecture of the database (Figure 4) within three dimensions with regard to control over the data source. The *component* comes as the first dimension as the company's technical capacity, which includes the necessary equipment and manpower to collect, compute, and then store the data. This equipment and facilities can be centralized in one place or distributed in different places with worldwide access.

The *development* as a second dimension includes technical aspects related to programming and implementation. It might be either developed by one central group across the whole organization or by collaborative interaction between all actors within the system. The *control* is related to the planning of the database system, it may be centralized to one function/facility. It is mainly centralized within the company that owns the system. This also has been referred by Grossman and Hart (1986) as the company residual right of control.

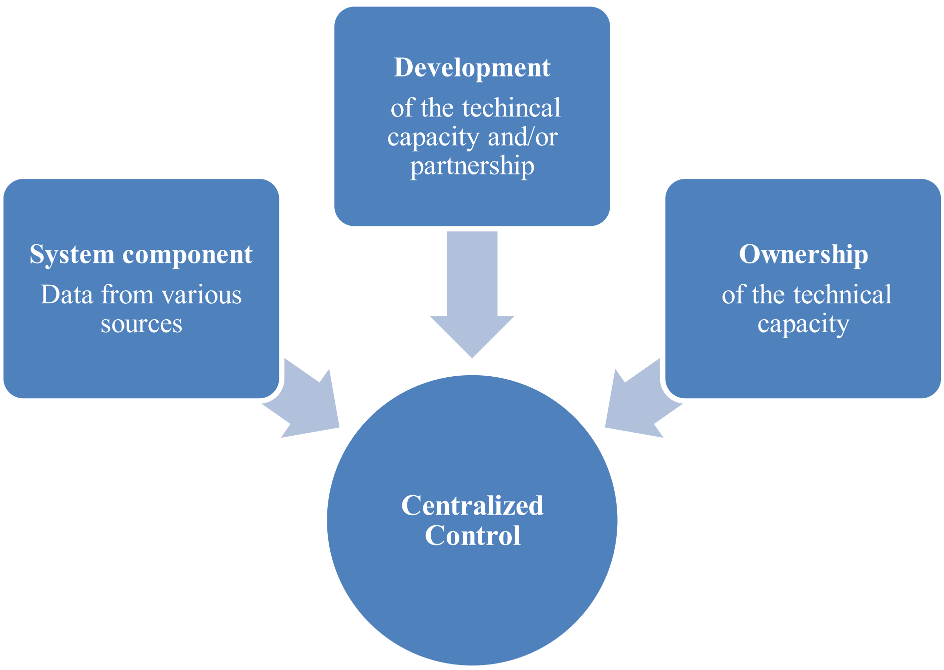

Figure 4. Data architecture and ownership. Adapted from Van et al. (1995)

The ownership of data is slightly different from the use of data (Van et al., 1995). Hence the ownership means the right to control and use by one centralized organization without giving the right to the outside access. Moreover, the right to own the data affect the process of value creation, which will open the pathways for the company internal management and decision-makers to increase their investment in the data sector. The usage right qualifies the company to access, edit, standardize and create data but it does not give the company "non-owner" the controlling right. However, the control can be decentralized if the connections between system actors happen through the chargeback system (Van et al., 1995; Grossman & Hart, 1986).

In the digitalized business environment, the flow of information between all actors in the business network is known as data sharing (Stefansson, 2002; Lewis & Talalayevsky, 2000). Stefansson (2002) argued, information technology supports the company's proprietary and shared data. In the proprietary data, the accessibility of database information will be available to the employees who have internal business needs. The shared data will be shared through communications with customers, business suppliers, and any other actors who are involved in the business operations. However, in the information technology-based systems, the data exchange is done through the Electonic Data Interchange (EDI); a special form of Inter-Organizational Systems (IOS) (Ramamurthy & Premkumar, 1995).

Iacovou et al. (1995, p. 466) defined EDI as *"co-operative inter-organizational systems that allow trading partners to exchange structured business information electronically between separate computer applications"*. Ramamurthy and Premkumar (1995), EDI eliminates human intervention and control over the data. It gives the possibility to automated the entire system, and then provide decision makers with precious information to forecast customer demand, penetrate sales rates, and generate quick responses for customer demands "either end customers or supply chain partners". Accordingly, Iacovou et al. (1995) identified four fundamental characteristics of EDI. The first element is the partnership between the business organizations, it should at least include two participating organizations. This will allow electronic data sharing and interchange between companies communication systems.

The second element is related to the processing of data between the participating organization, it should be supported by an independent system to exchange the data between all organizations. This is one of the unique elements that differentiate EDI from other communication systems, which allows multiple users to use a centralized application system. The third element concerns the data exchange between organizations, it should be covered by some agreements to protect the coding and formatting of the data. Then, the exchange of data between systems should be achieved through well-established telecommunication links.

Later, Ramamurthy and Premkumar (1995) study suggested a framework (Figure 5) for the adoption of fo EDI technology. Ramamurthy and Premkumar viewed the EDI system as a way for the company to realize a competitive advantage in the rivalry environment. The adoption “diffusion” process consists of two elements; the internal diffusion through the integration of organization internal elements including the functional and technical capabilities to support the implementation of EDI. It is important to have a flexible/or flat organization structure to support the implementation of the data interchange systems. Besides, the degree of innovation adaptability inside the organization itself and within the ecosystem as a big network of partnering organizations. Otherwise, it will be challenging to apply any innovation strategy. The external diffusion combines company efforts to integrate its suppliers and trading partners within the EDI system.

The inputs of this model are characterized by the degree by which the organization supports the innovation. As discussed earlier in the pathways to data monetization, the company must select the suitable pathway to leverage its analytical and technical capacity in order to support the transformation of information between its internal functions and external trade partners. These innovation factors are enhanced by the motivation of organization management towards innovation and the ability of the organization to adopt unconventional techniques. Afterward, business organizations will be able to monitor the outcomes of EDI adoption.

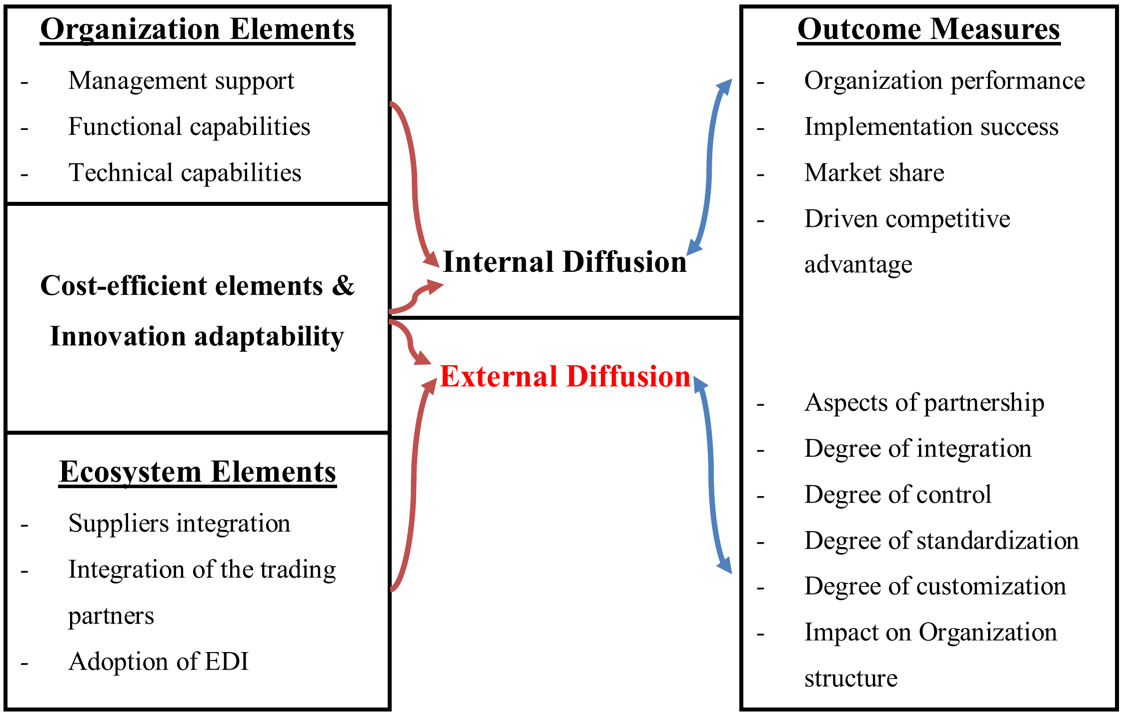

Figure 5. The Diffusion of EDI in the business organization. Adapted from Ramamurthy and Premkumar (1995)

2.1.4 Benefits of data sharing and EDI to the business organization

In the application of EDI, the business organization needs to have the capacity and system compatibility with the requirements of EDI application. This requires sufficient financial resources to invest in the firms IT infrastructure (Iacovou et al., 1995; Pfeiffer, 2012 pp. 108 - 109). Hence EDI requires organizational integration with the internal information technology system (IT) and the external system connecting the business with the supply chain partners. It adds value to the whole business channel connecting all partners and improves the transaction processes between partners (Ramamurthy & Premkumar, 1995).

On the managerial level, the integration of EDI with the IT system will enable the management board to identify the performance gap, then accordingly plan with other business partners to fulfill the requirements of those gaps. This approach will open the pathways for establishing a competitive advantage for the channel relationships either by expanding the current business network or establishing a long term partnership with business partners (Ramamurthy & Premkumar, 1995).

Consequently, O'callaghan et al. (1992, pp 46 – 45) identified three positive impacts of the EDI on the channel relationships. It enables faster transmission of data between all actors in the relationship, and then minimizes the waste by having shorter lead time than before, faster response to customer sales/purchase orders, and then cutting down the operating costs. Iacovou et al. (1995) argue; the electronic transmission of information provides shorter order lifecycle and reduced order costs.

Further, it boosts the greater accuracy and higher quality of the processed data because the human intervention is replaced by computer-to-computer or terminal-to-terminal system. Pfeiffer (2012, p. 108) related the accuracy to the elimination of manual paperwork system, that takes dozen of hours and have the possibility of attempting data errors. Then providing complete information about the business transaction, it allows the organization to provide greater services for the existing channel customers.

Based on Pfeiffer (2012, pp. 99 - 107), the accurate information enable the efficient business operations, which provide the company with the capacity to generate a time-oriented responses for customer needs, strengthen the relationship with trading partners through the accessibility of reliable information, and qualify the company to expand the business scope and compete in the foreign markets. Because the speed and accuracy in the transmission of information enable the company to integrate within the business scope, rapidly understand the prospect opportunities, and develop an advantage among business rivals (Iacovou et al, 1995).

2.2 Big data in the healthcare context

This chapter discusses the concept of big data in the healthcare system, the value creation in the service-oriented businesses “taking the healthcare system as an illustrative example”, the big data lifecycle in the healthcare system, analytics of healthcare big data, and the driven benefits to the healthcare industry.

Healthcare is considered a data-intensive infrastructure system that gives the possibility for healthcare users to access information generated by the major network (Khaloufi et al., 2018). Raghupathi and Raghupathi (2014, p.1) referred to big data in healthcare as "*the electronic health data sets so large and complex that they are difficult to manage with the traditional software and/ or hardware, nor can they be easily managed with traditional or common data management tools and methods*". Accordingly, big data adds value to the healthcare system and give convenience for users to use/manage their health-related information and cut the boundaries between user and operators (Tempini, 2017). Nambiar et al. (2013) argue; big data analytics in healthcare can optimize overall cost structure ranging from health providers including "small clinics, local health centers, and big hospitals" to the governmental level. Because the annual budget of healthcare system represents big challenges for some government especially when allocating the required budget for the healthcare system, that is required to balance between spending's of the system and the overall outcomes.

It can be challenging to manage the diverse and huge volumes of data in healthcare systems due to the complexity, and diversity of the generated data (Groves et al, 2013). Moreover, the big data concept is characterized by the huge volume of data, velocity in information transfer, and a variety of information types (Russom, 2011). In the healthcare, the new forms of big data generated information like 3D imaging and biometric sensor readings have shifted the healthcare system from being paper-based system into digital "cloud" system (Raghupathi & Raghupathi, 2014 p.3). The big data in healthcare is opening the doors for new research trends to find out the best ways on how to transform anonymous data to useful information that can be used as an input for other healthcare systems/applications. Ultimately, it provides healthcare providers with a meaningful support "information-based" to improve the care system, provide patients with the most convenient service, and cut down the operating costs (Jee et al., 2013).

Khaloufi et al. (2018), healthcare system generates a massive volume of data and it is extremely large for the normal analyses and storage techniques to deal with. Regardless the challenges of data security and information protection in the healthcare industry, the features and characteristics of big data analytics will help healthcare organizations to provide better care options and evenly open the pathways for a customized/individualized treatments options. Jee et al. (2013), the goal among all healthcare providers and governmental authorities is to provide easy and equal access for every single citizen. Therefore, effective techniques on the managerial and financial sides are needed to determine the priorities for each healthcare organization and explore the fitting managerial practices for the organization. In healthcare context; the top-down approach is recommended while dealing with big data, it breaks the system's big level into smaller segments "sub-systems" to gain useful insights and reach out the managerial decisions from the executive levels.

Jee et al. (2013), big data in healthcare are defined within the context of silo, security, and variety. Hence the silo is related to the confidential healthcare related information owned by certain government/healthcare authority. The security is highly ranked among other attributes of big data in healthcare; because healthcare providers are confined with the privacy of data, the authority to share the data and the legitimate ownership and privacy rights of users/patients. The variety of healthcare data refers to the existence of various forms of data generated in the healthcare sector. The data in healthcare can take various forms either structured, semi-structured, and unstructured format (Abiteboul, 1997). However, the data in the healthcare context tend to be popular in the structured format rather than the semi-structured and unstructured forms. Example, data generated from Electronic Patient Records (EPR) (Raghupathi & Raghupathi, 2014).

2.2.1 Big data value-creation in the service-oriented businesses (ex: Healthcare context)

Believing in the importance of big data analytics have given the opportunity to many grocery stores around the globe to shift from traditional inventory and stock management systems into digital data based system (Groves et al., 2013; Dunkley et al., 2004). By trading off between the cost of technology installation and its returns, a wide range of stores nowadays are using loyalty cards, which enable store managers to track customer behavior, identify sales trends, optimize the inventory level and tailor special offers based on customer preferences. Fortunately, it maintains customer loyalty (Dunkley et al., 2004). If we shift to the healthcare system, the comparison is equivalent. We will find a user who needs to use the care system, receive the best quality, and get the most convenient services. However, the nature of healthcare system is categorized by high resistance to the investment in information technology because of its high costs and there is no guarantee for high returns (Groves et al., 2013).

The service relates to the concept of value creation for the application of IT innovations (Lim et al., 2018; Berkley & Gupta, 1994; Lim & Kim, 2015; Rai & Sambamurthy, 2006; Watanabe & Mochimaru, 2017). While the information technology-based systems tend to digitalize information in form of huge datasets (Lim et al., 2007; Lim & Kim, 2015). Indeed, this huge sets of data are defined as big data (Fan et al., 2014), which is extremely large for the traditional processing techniques and it requires a newly developed system to analyze them (Jeble et al., 2018). Further, Jeble et al. (2018) suggested a conceptual framework (figure 6) for big data analysis and its impact on the decision-making process. Hence, companies apply new techniques in analyzing big data to gain fruitful insights for the well-informed decision-making process; and leveraging company competitive advantage as follows:

Develop data source: includes all collected data from traditional resources like customers data, suppliers data, and data obtained from enterprise resource planning systems. Therefore, the business entity needs to have the capacity for installing reliable information system infrastructure, that can collect a huge volume of data from multiple sources and analyze them later on (Fan et al., 2014).

Data mining and data analysis: the process of transferring the huge datasets into meaningful insights, that can be prepared through categorizing datasets based on the common patterns using computer-based statistical techniques. The analysis is done using statistical tools like SPSS, R software, SAS and similar tools are used to gain beneficial insights from the volumes of datasets.

Analytics: analytics in big data are categorized into three main categories; descriptive analytics, predictive analytics, and prescriptive analytics. These types of analytics help decision makers to gain significant insights from the collected data. In order to develop the organization’s capacity, introduce new strategies to acquire new customers or retain existing customers. The descriptive analytics synthesize the analytics based on the past data obtained from various forms of reports. It assists the managerial team to understand what happened in the past. Predictive analytics supports predictions "forecasts" based on the past. It helps decision-makers to predict their decision based on what happened in the past. Prescriptive analytics consists of several analytical tools like optimization, scenario analysis, and stimulations. These tools provide decision makers with prior knowledge of the expected outcomes and help in making well-informed decisions.

Decision making: big data analytics improve the overall ability of the decision makers to take a better decision, by which they aim to acquire new customers, improve customer loyalty, and increase the retention rates (Groves et al., 2013). Certainly, predictive analysis help decision makers to plan ahead, identify the right customer segments, and design the suitable offerings. Also, it helps in optimizing the inventory level, acquire forecasting for customer demand, and retention of the internal employees by improving the overall working environment (Provost & Fawcett, 2013; Jeble et al., 2018).

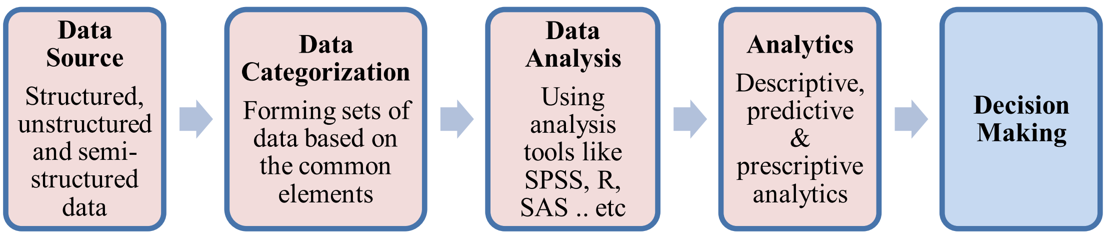

Figure 6. A roadmap to the decision-making process in the healthcare context. Adapted from Jeble et al. (2018)

2.2.2 Big data lifecycle and analytics in the healthcare context

According to Sinaeepourfard et al. (2016), big data is a complex data system that requires comprehensive analysis and managerial techniques. From the technical aspect the big data means Hadoop (Raghupathi & Raghupathi, 2014). The protection of data over its lifecycle is required to ensure the reliability and dependability of information being input for the healthcare organizations. Khaloufi et al. (2018) proposed a model (Figure 7) to address the main phases of the big data lifecycle in healthcare. According to Khaloufi et al. (2018), big data lifecycle includes four main phases:

Data collection as the first element of the big data lifecycle. In this phase, overwhelming volumes of data are collected from different sources in several forms. Raghupathi and Raghupathi (2014) data can be generated from different sources like data generated from Electronic Patient Records (EPR) and machine-generated data, which include medical imaging reports, laboratory reports, and prescriptions. In addition to the insurance and administrative reports. In this phase, the spoofing or spamming of data represents a threat to the medical organization. Thus, the highly secured database systems are required to protect the data from non-authorized access.

Data transformation that includes filtering and classifying the collected data based on data structure “structured, unstructured, or semistructured (Abiteboul, 1997)”. The filtering improves the quality of data – to be ready for the analysis - either by identifying the missing datasets or removing the unneeded data “noise”. Organizations need to establish a multi-authentication and verification system in order to protect any possible content-based attacks.

Data modeling is the analysis phase, known as data mining which uses several analysis techniques like clustering, classification, and filtering to examine the relationships and connections between datasets, then provides reliable inputs for the information-oriented decisions (Fayyad et al., 1996). Ex: Collaborative Filtering (CF) technique, which used in recommendation systems to help users to select between relatively similar items (Koren & Bell, 2015). Then, the knowledge creation as a last phase in the lifecycle model, the verified information will be stored in the database system to be used by the decision makers. High sensitivity and privacy issues are the main characteristics of the healthcare data (ex: patient records data). Thus, healthcare organizations need to use highly secured systems (authentication based systems) and encrypt the data using the matching algorisms.

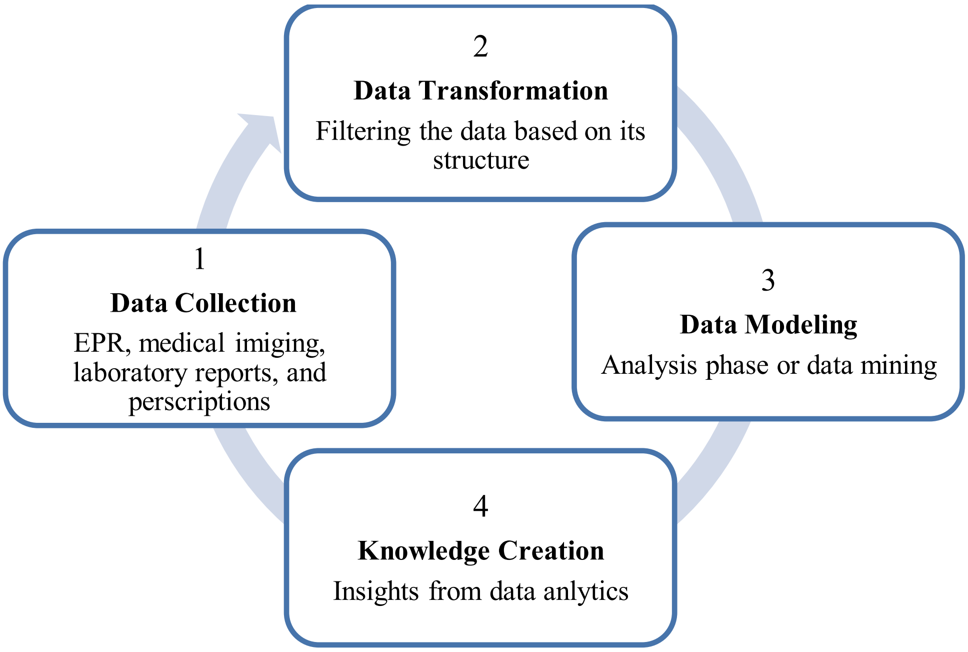

Figure 7. Big data lifecycle in the healthcare context. Adapted from Khaloufi et al. (2018)

Big data analytics in the healthcare context

The healthcare system is controlled by some forces like laws, governmental policies, data privacy, and patient concerns about the cost of and quality of care (Raghupathi, 2016). However, there is a need for using big data analytics in segmenting the patient database, which will help in detecting diseases in early stages where the treatment policy can be more easy and effective, improve the response rate, minimize the waiting times, help patients to select the fitting care protocol that suits their status the most, early detections of frauds if happened, and provide an overall high quality reliable healthcare services and cutting down the operating costs (Groves et al., 2013; Raghupathi, 2016).

LaValle et al. (2011 p.3) *"Organizations that know where they are in terms of analytics adoption are better prepared to turn challenges into opportunities".* Accordingly, Raghupathi and Kesh (2007) argue, the volumes of big data are complex and require the application of specialized skills to be analyzed. Hence the healthcare is considered as data-intensive infrastructure (Tempini, 2017). Indeed, the analytics of big data in healthcare is similar to the analytics process of any big data-based system, the difference lies in the application of the analytics techniques in terms of improving the quality of the Electronic Patient Records (Raghupathi, 2016).

Raghupathi and Raghupathi (2014) suggested a conceptual framework (figure 8) for big data analytics in the healthcare sector. As the big data is characterized by the huge and complex volumes of data, which need to be divided into several nodes to be able for the analysis processes. The cooperation between hospitals as the owner of data; and business organization represented in the companies that have the analytical and technical capacities to process the data is defined into four main steps. The first two steps are related to hospitals, as they have the legal responsibility of collecting, filtering and anonymizing patient data. Then, the processing and analysis of patient data are related to the business organizations that have the analytical and technical capacities to analyze the data. As defined by Raghupathi and Raghupathi (2014), the analytics process goes as follows:

Big data source: raw data in healthcare comes from internal sources (like medical prescriptions, patient support data, or health records) and external sources (like insurance companies generated data, governmental data, external laboratory reports, and pharmacies data). The data can be generated from multiple other sources like web and social media data, it includes data generated from smart devices and social media platforms like Facebook, Twitter, Instagram, etc. The Machine-to-Machine data is the data generated from several devices like meters and sensors. The big transaction data contains claims, bills, and reimbursement generated records. The biometric data includes medical imaging, laboratory digitalized tests, fingerprints, X-rays, etc. Besides, the human-generated data which includes both unstructured and semi-structured data like medical prescriptions, emails, and other similar documents.

Big data transformation: preparing the raw data to be processed. Raghupathi and Kesh (2007) argue, the data warehouse is one of the available options, where the data from several sources is combined then categorized based on its type whether it is structured or unstructured data, then it will be ready for processing.

Big data platforms and tools: Raghupathi and Raghupathi (2014 p.6) defined Hadoop as "*the most significant platform for big data analytics*". Hadoop is open source software, that is designed for the distributed processing of large data sets across clusters of computers using simple programming models. Thus, Hadoop enables the players in the healthcare industry to store and analyze the massive amounts of data that were very challenging to be handled before.

Big data analytics and applications: the applications of big data analytics include queries, reports, Online Analytical Processing (OLAP), and data mining. It helps healthcare providers to gain useful insights from the complex datasets to make well-informed decisions and improve the overall quality of the healthcare system. It assists doctors and nurses to track patient status before and after treatments.

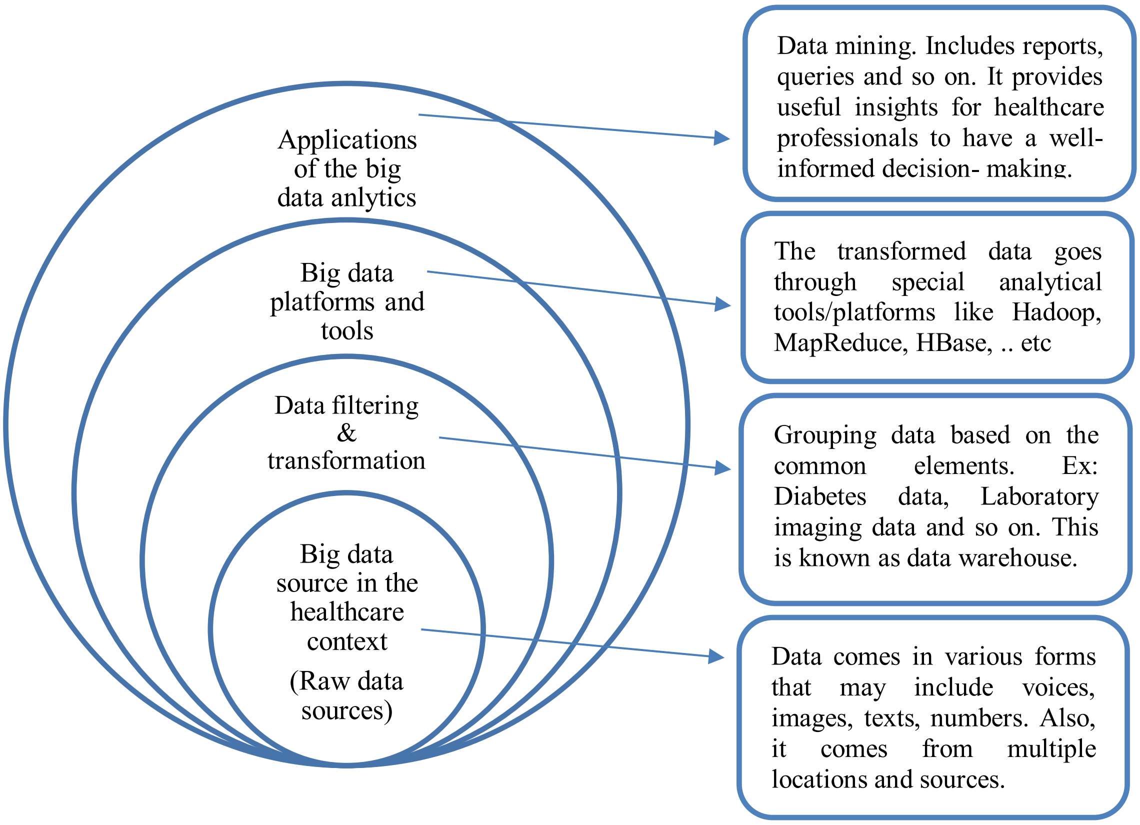

Figure 8. Big data analytics in the healthcare context. Adapted from Raghupathi and Raghupathi (2014)

2.2.3 Benefits of the big data and its analytics to the healthcare

Healthcare industry is known to be one of the most generators of high volumes of data every year around the globe, which still kept in hard copy from within the majority of hospitals around the globe. This happens because the quality of data and accuracy of the provided information is connected to life or death decisions. Taking an example, poor physicians handwriting may lead to the delay in acquiring the necessary medication, which may lead to the development of the disease/infection patterns (Raghupathi & Raghupathi, 2014). Big data analytics in healthcare will provide the system with new algorithms, that can look for common patterns in the patient's history. Then it will help physicians to predict the disease group, reduces the waiting queue for patients, and reduces the time of stay in hospitals (Jeble et al., 2018; Shein, 2012). Moreover, big data generated algorithms can correlate the change in patient's behavior to infection, and that will help hospitals emergency services to rescue the severe cases quickly (Jeble et al., 2018).

Healthcare is becoming a promising field for big data analytics and applications. Ranging from analyzing patients disease history, tracking the outbreaks times if expected, and monitoring the post-treatment procedures (Raghupathi, 2016). On the insurance side, insurance companies generate a massive amount of data either in reimbursement of patients claims or tracking patient's health status. This massive amount of data represent triggers the necessity for introducing new healthcare system based on big data analytics (Raghupathi & Raghupathi, 2014; Lim et al., 2018).

Lim et al. (2018) define healthcare as an information-intensive service, which generates information from day to day patient records. This data comes from patient history, physicians prescriptions, pharmacies records, laboratories and medical imaging reports, and administrative data reports (Groves et al., 2013). The need for this data comes in compliance with the requirements of healthcare systems, insurance requirements, country's laws and regulations (Raghupathi & Raghupathi, 2014; Raghupathi, 2016). The shift towards big data analytics and its applications is necessary to save lives, enable healthcare nurses and physicians to make informative diagnoses that can cut down the operating costs, improve the care and treatment system, speed up insurance related procedures, help/improve the decision making process, and connect all healthcare units within certain system with a digitized medical records. Indeed, this can open the pathways for remote diagnoses and early diagnoses and treatments in the case of emergent situations (Raghupathi & Raghupathi, 2014; Lim et al., 2018; Groves et al., 2013).

2.3 Business models

There are continuous research trials attempting to understand the concept of business models and the evolvement which happens over time (Osterwalder et al., 2005). Indeed, the business model is a great planning tool which aims to coordinate between the system's different functions to covert the available resources into capabilities, and then create and deliver the value. Accordingly, the business model allows the business to operate as a system (Magretta, 2002). This chapter discusses the definition of the business model and the emergence of the business model concept.

2.3.1 Definition of the business model

Osterwalder et al. (2005) described the business model place in the company as the starting point of doing the business. It is the company approach is realizing the new business opportunities, that will open the pathways for generating innovative business ideas and developing new patterns for creating values for customers (Chesbrough, 2007). According to Ahokangas et al. (2014, p.265) business model is an architectural tool which enables the easy visualization of organizational capabilities and competitive advantage. The business model - as a tool for capturing and capturing the value - contains nine elements: value proposition, customer segments, channels, customer relationships, key activities, key resources, key partners, cost structure and revenue streams.

Business models are the company strategy to generate money and sustain the continuity of its business practices by creating value for customers and developing a competitive advantage for the company in the certain market/industry (Ovans, 2015; Osterwalder et al., 2005). Accordingly, Osterwalder et al. (2005) suggested the business triangle framework (Figure 3) illustrate the concept of the business model inside the firm. According to the business triangle, the business model takes a central role in building a relationship between business strategy, the organization itself, and technology forces. Certainly, the business model is still subject to external forces like laws and regulations, competitive forces, pressures of the social environment, rapid technological changes, and changes in customer demands.

Chesbrough and Rosenbloom (2002) business model act as a mediator between the business technical domain –inputs– and economic domain –outputs–. In between the technical and economic domains, there are multiple external factors that impact the business system. As shown in (Figure 9), these factors are characterized by market competitive forces and uncertainty (Osterwalder et al., 2005). However, the mediation role of business model tries to sustain and facilitate the business practices through commercializing business core value and generating responses for customer requirements (Prahalad & Bettis, 1986).

Figure 9. Business model definition. Adapted from Osterwalder et al. (2005)

Chesbrough and Rosenbloom (2002 p.535) argue "*The business model starts by creating value for the customer and then constructs the model around delivering that value*" Accordingly, the business model can be viewed as value creation system, which allows different business functions to fit and work together as a system (Magretta, 2002), that enable businesses to overcome the competition, built business competitive advantage, and commercialize business values to the targeted customer (Osterwalder et al., 2005). Based on the value creation concept, the business model tries to understand the customer segment, the different aspects by which they evaluate the value, and ultimately finding the strategy to communicate this value with customers accordance with company cost structure (Ovans, 2015).

The business model is considered as a connecting link between business strategy, business processes, and the information system (Figure 10), which represent the main building blocks for the business models (Pateli, 2003; Iivari et al, 2016). Yet, the business model helps the company to understand the core of its business. On the contrary, it can be a challenging way that use a huge amount of company resources to understand this core value. Because the majority of business models concepts are still firm-centric “not ecosystem-oriented” which is not applicable for an interdependent ecosystem. The ecosystemic business opens the pathways for innovation and growth of companies involved within the system (Iivari et al., 2016). The ecosystemic business model transforms the business processes into a structured cooperative network. Indeed, the ecosystemic approach enables multiple business organizations to work as a system which requires cooperation and integration of organizations capacities to create value; and then deliver the value to the customers (Moore, 1993). Gomes et al. (2017) the ecosystemic business is a set of interdependent activities, that establish linkages between the business organization and its partners through three phases: opportunity exploration and exploitation, value creation and capture, and advantage exploration and exploitation.

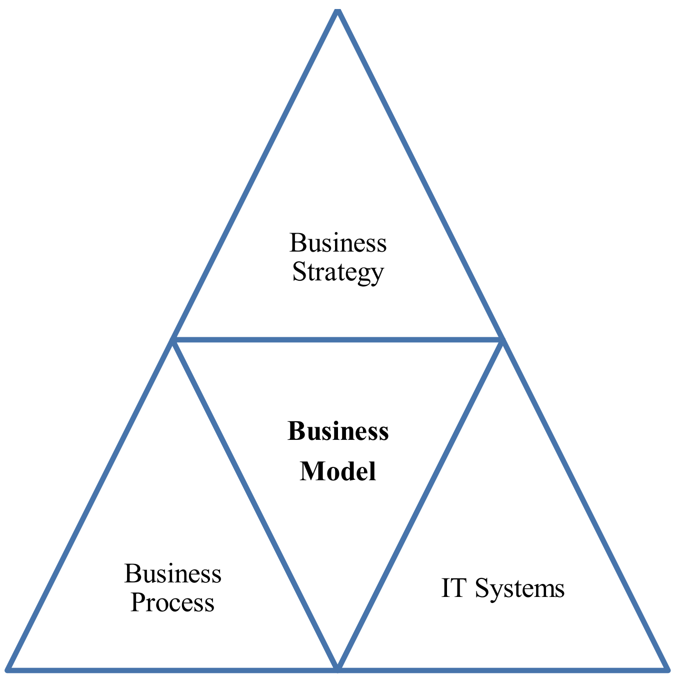

Figure 10. The building blocks for the business model. A adapted from Iivari et al. (2016) and Pateli (2003)

2.3.2 Business models in the digital setting

Recently, business models are shifting from being value chain-oriented business models towards ecosystemic business models. This shift drives business organizations to choose between having the dominant control over the value chain or being a part among complex ecosystem that contains several business actors working together to create and deliver the dominant value for the end customer (Weill & Woerner, 2015; Bharadwaj et al., 2013). Wirtz et al. (2010, pp. 274 - 276) classify the internet-based business models into four categories of internet business models (Figure 11).

The content-oriented business models: Ex. The Independent. This model is used by firms that build their business concept around content creation. These firms collect, select, and distribute the relevant online content via their websites/portals. Accordingly, the value is created around providing an updated, user-friendly, and convenient content for their customers. The revenues are generated directly via premium accounts or indirectly through advertising Ex. Native advertising and Sponsored Ads.

The Commerce-oriented business models: the model is based on providing a cost-efficient place for sellers/buyers to exchange their goods and services. It focuses on the initiation of the business transaction, providing suitable payment options, and delivery options. Ex. Amazon provides buyers and sellers with an online convenient platform to use it for buying/selling goods, comparing between available options and providing both parties "buyer and seller" with trust and confidentiality; especially when it comes to the security of customer information. Then, Amazon generates its profits from its own sales and commissions from its users.

Context-oriented business models: like the content-oriented business models, the revenues are usually generated from online advertising. Ex. Google is are trying to filter online information, reduce complexity, and increases the transparency of the available information. Ultimately, Google helps its users to easily navigate the internet and get the most convenient online experience.

Connection-oriented business models: firms provide customers with the option of getting the physical and/or the virtual network infrastructure. Ex. EarthLink provides an interconnection level to its customers through communication, web hosting, emails, and privacy and data security products and services.

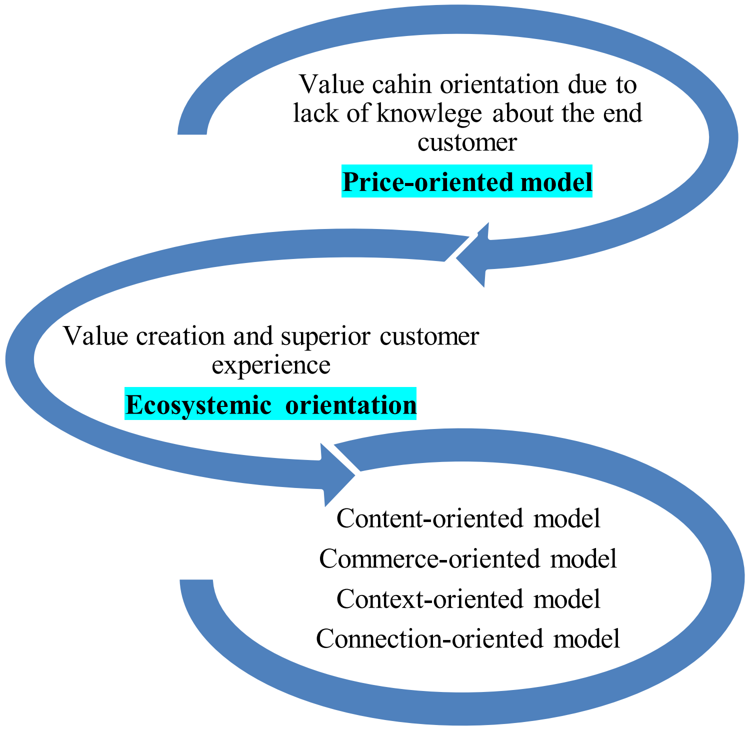

Figure 11. Development of the business model thinking. Adapted from Wirtz et al. (2010) and Iivari et al. (2016)

Another study by Weill and Woerner (2015), suggested four types of business models in the digitalized business environment (Figure 12). The supplier model, where suppliers have the most partial knowledge about the end consumer, but they operate within the value chain of another company. Thus, the supplier does not have the dominant power over the value chain, but they have the knowledge of their end customers. The business organization "value chain leader" move towards digitalization represent some challenges on the suppliers part "less powerful actor". The model enhances the flat growth and consolidation of the industry "acquiring and merging small supplier under the control of the value chain leader". Suppliers in this model are more likely to operate under the pricing pressure; because they do not have the best knowledge about the end customers. In the meantime, customers are having different online available options and they are more likely to choose between the cheapest alternative.

The omnichannel model is known as a “multichannel model” which requires complete knowledge about end customers. The big data and its analytics represent a meaningful input for understanding end customer requirements. Indeed, the extensive knowledge of customers needs to enhance companies to gain more knowledge about customers and analyze their behavior (Ex. Analytics of Facebook pages and website metrics). Accordingly, companies tend to re-design their organizational structure based on the extensive knowledge and understanding of customer needs, which helps in building a long lasting relationship with customers and attracting new ones. The omnichannel model provides customers with a verity of touchpoints including physical stores and the digitalized e-commerce portals.

In the ecosystem driver model, network actors have complete knowledge of end customer needs and a wide network of integrated suppliers. The model provides system participants with a platform to conduct their business. Taking Amazon as an example, they allow individual users to sell their products via Amazon. The products can be a complementary part to Amazon offers or a competing force for its offers. Likewise, the omnichannel model, the companies in the ecosystem driver model try to own the customer relationship and provide dominant customer experience. It is also known as a customer-centric model. In this model, customer feedbacks and ratings represent vital inputs for the company and its suppliers to improve their services, strengthen their brand, and generate more revenues.

The little knowledge of the end customers in the modular producer model forces the business organization to get external help in the consumer knowledge side. Because they need to know more about customers, and then design their business process accordingly. The modular producer model is known as the plug-and-play model, which helps the producer to adapt to different ecosystems. Because of the intense competition and the availability of other alternative options, the innovation and rapid adoption to customer requirements are needed to guarantee the continuity and success of the business operations.

Knowledge about the end customer (Extensive – Low)

Extensive	**Multichannel Business Model** Having an extensive level of customer knowledge enables organizations to offer a wide range of products/services to meet customer requirements. Requires the business organization to establish a multichannel business relationship to provide customers with multiple touchpoints; including both physical touch points and digitalized touchpoints	**Ecosystem Business Model** The interdependency between system actor enables every partner in the business relationship to have extensive knowledge and a better understanding of the end customer requirements. The model tries to match customer needs by applying a customer-centric model strategy, that uses the customer as a focal point for the overall business strategy.
Low	**Supplier Business Model** Having low knowledge about the end customer force companies to operate within the value chain of another dominant company; which have the required level of knowledge about customer requirements. The innovation levels are very low; because the supplier does not have the same level of power as the value chain leader.	**Modular Business Model** Having a low level of knowledge about the end customer requirements enable companies to adapt to any ecosystem. The ecosystem should be aligned with company goals and scope. The plug and play model enables companies to easily adapt new innovations, market requirements.
	Value Creation	**Ecosystemic context**

Business Model

Figure 12. Business models in the digital context. Adapted from Weill and Woerner (2015)

2.3.3 The ecosystemic business and healthcare system

As mentioned in the previous chapter, the business model describes the way of doing the business. In terms of identifying the strategic way of capturing the business opportunity in a certain market, and then creating and delivering the promised value (Osterwalder et al, 2005). Thanks to the development in information technology and big data analytics; the speed of transforming information across the network nodes has improved and the transaction costs have cut-down to the minimums (Jeble et al, 2018). Accordingly, business organization have to establish new platforms to access information, sell information, or evenly analyze customer behavior (Loebbecke & Picot, 2015).

Hence digitalization has not only changed the way of doing the business but also introduced new concepts like the ecosystemic businesses (Bharadwaj et al, 2013). According to Iivari et al., (2016), the ecosystemic business refers to the complex network of interdependent business organizations. This networks may include cooperation between the internal and external business partners, non-commercial stakeholders, universities represented in the spinoff activities and its research-driven innovations. This cooperation aims to make the best use of organizations capabilities and resources to provide a fruitful environment for creating new innovations and establish a superior competitive advantage.

The digitalization and increased adoption of information technology have enabled the connectivity and ease of information transfer between business functions (Gomes et al., 2017; Wootton, 2001). Yet, technology-driven innovations like smart computing and big data analytics transformed the structure of the firm-centric business model. It becomes more challenging for the centric business organization to meet the market requirements nor even create the value. Accordingly, the cooperation between the business organization and its partners, suppliers, and customers is an essential element for creating cooperative networks. It will be able to intensify the decision making and value creation processes (Iivari et al., 2016).

Hence the integrated technology is transforming the healthcare industry from a traditional face to face caring system "requires the physical existence of the patient" into information exchange smart systems. Smart systems cut-down location boundaries by enabling physicians and patients to get connected from their homes, offices, or evenly through phone calls which are known as telemedicine. Wootton (2001) defined telemedicine within the context of any medical activity that involves the element of distance. According to Perednia & Allen (1995, P. 483), telemedicine is the use of telecommunication technology to provide the medical services at any place within any time. This mainly depends on the usage of electronic signals to transfer information from one site to another. Indeed, telemedicine is a new diagnostic tool that can be implemented to enhance the use of information technology in the healthcare sector and provide the most convenient healthcare services for the patients and other customers.

Wootton (2001) the communication between physicians and patients happen with the help of telecommunication technology, that enables patients to get a piece of immediate medical advice. The effectiveness of implementing the telemedicine technology on a larger scale is debatable; especially from the cost-effectiveness perspective. Because it will require a huge start-up cost to install the system. Ex. The installation of equipment that can directly transmit digital x-rays photos to physicians and radiologists anywhere. On the contrary, it can minimize the waiting time required to admit patients to hospitals. Ex: in case of remote consultation between public health nurses, general practitioners, and specialists. Gomes et al. (2017) argue the connected health model is a mean for transforming the healthcare system. Yet, it is an information user-centric model, that tries to bring together the system users "patients" and healthcare system including organizations and health professionals via the Internet of Things (IoT).

The discussion in the previous chapters focused on how digitization changed the traditional ways of doing the business. Magretta (2002) argued; a business model is a tool that describes how the external and internal elements of an organization fit together to coordinate the business activities, convert resources into capabilities, and then deliver the promised values to customers. Osterwalder et al. (2005) define business models as a tool for visualization the business logic of the organization. It helps the managerial team to easily communicate business values and aims with stakeholder. However, the information technology opened the doors for innovative ideas in transforming the structure of business activities and the ways of creating values. The idea of resource sharing becomes popular and demanding than before (Ritter & Schanz, 2018).

To go further and identify the business model framework for the sharing economy, a definition of the sharing concept is required. According to Oxford dictionary (2019), the word "share" is defined as *"A part or portion of a larger amount which is divided among a number of people, or to which a number of people contribute*". Thus, sharing means dividing a bigger item into small parts in order to make the best use of it. Whilst sharing in the business context is related to the concept of ownership and related rights. It means taking off the ownership rights and overcoming the centralized managerial approaches (Demil et al, 2018, Ritter & Schanz, 2018). Sharing gives the possibility for the network actors to aggregate around a major sharing center. It allows cheaper access to the service, promotes efficiency, and consistency to the business process. Further, it enhances the sustainability of resource use, because sharing means extending the lifespan of the resources and using it until the end (Ritter & Schanz, 2018).

Relating the previous discussion to the healthcare context, several researchers identified the process of data commercialization within the context of Software-As-A-Service (SaaS) (Ma, 2007). Further, classified the goods and service into three categories; the financial goods including financial assets. Ex. Cash. The physical goods like physical products that include durable and non-durable goods. Then, the intangible goods like software products that are included within the category of SaaS. From this perspective, the data falls in the third category – intangible goods – which can be commercialized using the concepts of SaaS. According to Ju et al, 2010; Ma, 2007), SaaS business models are defined as a new emerging model for the software industry, which provides software accessibility from the user's own computer. Accordingly, Ju et al. (2010) classified the SaaS business models as follows:

- Accessed via web model: enabling the end user to access the software application via a standardized web browser.
- Vendor support model: software developers take the responsibility of hosting and managing the software system. Therefore, the information technology department does not take an active role in managing this system.
- Subscription pricing model: monthly fees are paid depending on the usage and package purchased.
- Low customization model: the system is standardized for a wide range of customers, but a low level of customization is applied.

- Managed upgrades model: functions of the system are controlled by the vendor. The times of updates or system upgrades are determined by the vendor at specific times within the year.

2.4 Literature review synthesis

The literature review part is conducted to develop a platform the big data business models in the healthcare system. To be able to understand the related concepts and develop the framework for the study, a research question was formulated to cover the possible aspects of the framework as follows:

How to link big data and business model thinking in the healthcare context?

In order to be able to answer the research question, the concept of big data and its characteristics were studied. As discussed in the beginning, the big data refers to the large volumes of data, that have three main attributes: volume, velocity, and variety. The volume refers to the terabytes and petabytes amounts of data, the velocity refers to the high speed of data generation and analysis, while the variety relates to the different types and forms of data like images, audios, digital medical records, numbers, and many other forms.

Further, the relative concepts concerning data monetization and data ownerships were discussed from several perspectives. Either forming the required technical infrastructure at the beginning or developing the organization's analytical capabilities. In addition, the challenges and benefits of data monetization. The concepts related to data ownership and Electronic Data Interchange (EDI) were studies to formulate a comprehensive understanding of the data sharing cycle. Further, a connection between the big data and healthcare system is done to identify the main key elements connecting the concept of big data with the healthcare context. Afterward, the concept of business models was studied from different perspectives, especially from the notion of sharing and ecosystemic business contexts.

To draw a comprehensive synthesis for the theoretical background, the author summarized the main characteristics of big data in (Table 1) and the characteristics of ecosystemic business models in (Table 2). Then, combining these characteristics together in (Figure 13) to provide the research framework for the big data business models.

Table 1. Summary of the main four characteristics of the big data

Big Data	
Centralized Control "Residual right of control" (Najjar & Kettinger, 2013; Van et al, 1995; Grossman & Hart, 1986; Ramamurthy & Premkumar, 1995)	- The planning and control of the database system are centralized to one central function/or business organization. - The access of data is distributed to several places worldwide. - The company "centralized repository" should have the required technical capacity to collect, process, and store data. - Storing big data in a centralized repository allows better control over the data, maintaining the flow of the ongoing and outgoing data, and then helping to improve/speed the decision-making process.
Platform for Sharing "Access vs. Ownership" (Stefansson, 2002; Van et al, 1995; Iacovou et al, 1995; Ramamurthy & Premkumar, 1995)	- Allows trade partners to electronically exchange structured business information between sperate computer applications. - Enables faster transmission of information between all actors in the relationship through Electronic Data Interchange (EDI). - Cuts down the operating cost and shorten the data transmission lifecycle.
High level of integration "Channel relationships" (Pfeiffer, 2012; Ramamurthy and Premkumar, 1995)	- Integration between internal organizational functions and external trade partners enable the management team to quickly identify the performance gaps and cooperate with industry partners to solve them.
Consistency and Efficiency to the Business Process (Pfeiffer, 2012 pp. 99 – 107; Iacovou et al, 1995)	- Analytics of big data provides complete, accurate, and reliable information about business transactions. It enables speed transmission of information between business channels. - The high level of accuracy in big data analytics enables efficient business operations in forms of: 1- Time-oriented responses for customer needs "including business partners". 2- A strong relationship with the supply chain partners. 3- Expanding business scope "operating in foreign markets and generating a rapid response for market competitive power".

Table 2. Summary of the main four characteristics of the ecosystemic business models

Ecosystemic Business Model	
A platform for value capture and creation (Iivari et al, 2016; Gomes et al, 2017; Wirtz et al, 2010; Weill & Woerner, 2015; Pateli, 2003 pp. 337)	- Business models are created to capture values, and then construct the organization's capabilities to deliver these values. - The ecosystemic business consists of a set of interdependent activities, that establish linkages between internal business functions and external trade partners. - The exosystemic context enhances innovation and growth of companies involved in the system. - The system gathers all possible information about customers to ensure the best customer experience.
Speed in information transfer (Iivari et al, 2016; Loebbecke & Picot, 2015; Ma, 2007; Ju et al, 2010)	The complexity and interdependency between the ecosystemic actors enable: - Accessibility of information through special platforms like Software-As-A-Service (SaaS). - End user to get full access for the software application through a standardized web application. - Minor customization based on the end user needs. However, the overall system is standardized across the whole system.
Integration between system actors (Demil et al, 2018; Ju et al, 2010; Ritter & Schanz, 2018)	The integration between all actors in the ecosystemic business context enables: - The aggregation around one major sharing center. - The sustainability of resource use by expanding the resource lifespan "using resources until the end of its lifespan". - Cheaper accessibility for services and promotes efficiency and consistency of the business process.
Consistency and Efficiency to the Business Process (Wirtz et al, 2010; Iivari et al, 2016; Loebbecke & Picot, 2015)	The business model is created to reflect the operational and output system of the company. Accordingly, within the ecosystemic context. The integration between system actors that are represented in co-operation between the internal and external business partners, noncommercial stakeholders, universities represented in the spinoff activities and its research-driven innovations enables: - Transformation of traditional business activities into innovative context. - System users "customers/trade partners" to easily get access and integrate within the business process. - Transparency and consistency throughout the system.

2.4.1 The research framework for the big data business models

As discussed earlier, this study aims to identify and establish a link between the big data and business model in the healthcare system. To approach the platform for the big data business model, a summary of the main elements for the big data and ecosystemic business models were conducted in table 1 and table 2 respectively. Further, the examination of the common elements between big data and ecosystemic business model is conducted in (Figure 13) to identify the links between big data and business model and provide a road map for the empirical study part.

Ecosystemic business model (Adapted from table 2)	**Consistency and Efficiency to the Business Process**	?	Minimize Transmission Lifecycle	Minimize Performance Gaps	**A platform for Big Data Business Models**
	Integration Between System Actors	?	Value-Based Channel Relationship	Sustainable Business Process	Minimize Performance Gaps
	Speed in Information Transfer	Standardized Accessibility	Low Operating Cost	Cost-Efficient Service Offering	Innovative Business Processes
	A platform for Value Capture and Creation	?	?	Value-Based Channel Relationship	Superior Customer Experience
		Centralized Control	**Platform for Sharing**	**High Level of Integration**	**Consistency and Efficiency to the Business Process**
	Big Data (Adapted from table 1)				

Figure 13. The research framework for the big data business models

In the research platform for the big data business model (Figure13), the vertical elements – on the bottom of the table – represent the major elements for big data. The horizontal elements – on the left side of the table – represent the major elements for the ecosystemic business model. By combining the elements from the vertical and horizontal sides, the intersection between the vertical and horizontal elements was identified and labeled respectively as follows:

Minimize the performance gap: the integration between system actors enables the business organization to complement the areas of operation and performance gap. It enables all system actors to work together in providing an overall system that complies with customer requirements (Iivari et al, 2016; Gomes et al, 2017).

Minimize the transmission lifecycle: as discussed in the sub-chapter 2 about the big data lifecycle in the healthcare context. The full integration between internal and external business functions will enable; shorter time for transforming the collected data between system nodes, cut-down the required time for data analysis to the minimums, and speed up the process of value creation (Iacovou et al, 1995; Ramamurthy & Premkumar, 1995).

Value-based channel relationships: the shifts from the value chain system to value creation system enables the business organizations to adapt to different business models to comply with customer requirements (Weill & Woerner, 2015; Bharadwaj et al., 2013). As discussed in the sub-chapter 3 of the business models in the digital setting; companies are able to adjust to different models based on the content, commerce, context, and connection (Wirtz et al, 2010).

Sustainable business process: full integration between internal and external system actors enables the sustainability of resource use. It means making the best use of the resource until the end of its lifetime (Demil et al, 2018; Ju et al, 2010; Ritter & Schanz, 2018)

Standard accessibility: the centralized residual right of control enables the central business organization to distribute and grant the standardized system access through the web application (Van et al, 1995).

Low operating cost: the distributed system enables the business organization to complement the missing components from other actors involved in the relationship. Accordingly, it optimizes the operating costs to the minimum as companies will not have to develop all required capacities at the same time (Stefansson, 2002; Van et al, 1995; Iacovou et al, 1995; Ramamurthy & Premkumar, 1995).

Cost-efficient service offering: As a result of the low operating cost element; the ecosystem will be offering a cost-efficient product/service (Iivari et al, 2016).

Innovative business process: the integration between the internal business functions; including the technical and/or analytical capabilities with external business functions "partners" enable the business organization to easily adapt to the information technology requirements and provide an innovative offering (Weill & Woerner, 2015; Gomes et al, 2017).

Superior customer experience: the fulfillment of the previous elements will help companies to create and deliver a promising value for its customers, that will guarantee customers will get the most convenient experience.

The question marks (?) are related to the ownership concept. However, we need to check this concept from various aspects of the empirical study part. The following chapter discusses the research methodology and case companies that are used to examine these common elements and identify the missing ones.

3 RESEARCH DESIGN

The qualitative case study research approach is adopted in this exploratory study, to identify the platform for big data business models in the healthcare system. The context of this chapter discusses the research methodology, context, and quality of the research, sampling, data collection, and analysis method.

3.1 Research methodology

This research follows an interpretative qualitative research approach. Accordingly, this study does not follow any hypothesis model to test the research data and generalize the findings. However, the interpretative approach is applied to this phase of the exploratory research to link between the big data and business models in the healthcare system. Wellington and Szczerbinski (2007), the exploratory phase starts with identifying the relevant research questions concerning the phenomenon of the research. In this research, a major research question is identified "*How to link big data and business models thinking in the healthcare context?"*. Then the literature review was conducted to address the previous and current research efforts concerning the phenomenon of the research. Further, the themes for data collection were based on the concepts adapted from the literature background discussion in the previous chapter.

Yin (2003) the exploratory research is used to explore the phenomenon that does not have clear outcomes. Yet, to qualify for this research approach; the problem of research should do not have a clear solution. Because the exploratory research aims to increase the knowledge of academic researchers and industry experts concerning certain phenomenon. Accordingly, this research uses the exploratory approach because the links between big data and business model have not been clearly identified. Chesebro and Borisoff (2007), the qualitative research approach gives researchers the likelihood to examine various social phenomenon based on the viewpoint of the participants, and then gain a deep understanding of the research phenomenon.

Meanwhile, Miller and Yeo (2015), defined qualitative research as a descriptive way of analyzing individuals, organizations, or phenomenon. The interpretative approach is followed respectively in designing this research structure, starting with the literature background to formulate an overall understanding of the existing literature, and then identify the main elements for analyzing the study model "big data business model". Afterward, the research selecting the research approach is defined in terms of identifying the case companies, data collection method, and then the data is analyzed respectively (Figure14). The data analysis and findings are discussed in chapter 4, then followed by conclusion in chapter 5.

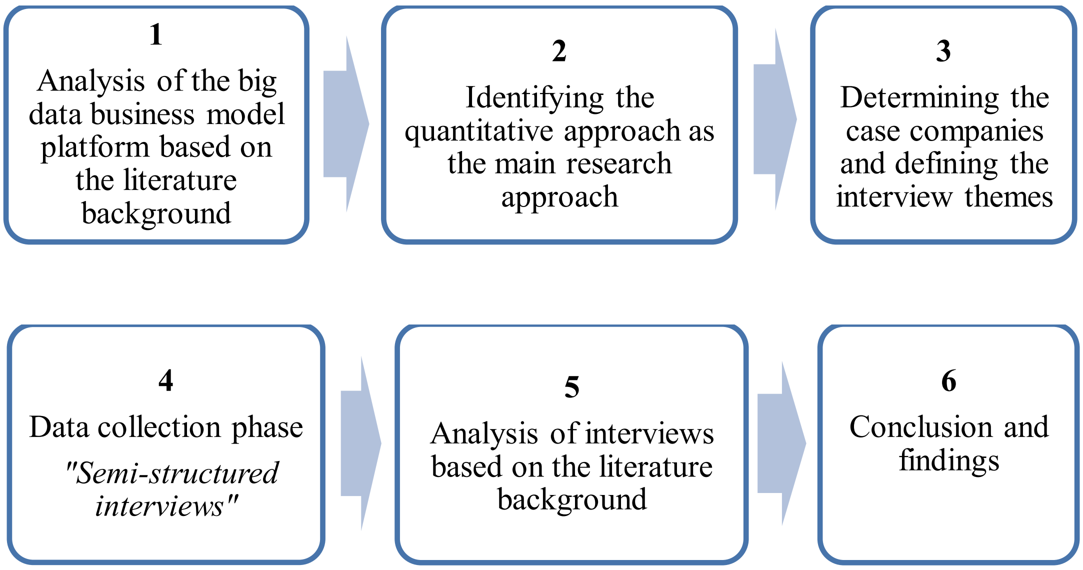

Figure 14. A roadmap to the empirical study

The word qualitative is defined in the Oxford dictionary (2019) as an adjective related to the act of measuring the quality of something rather than its quantity. According to Frey et al. (1992), qualitative research deals with narrative data that takes the form of words, not numbers. Accordingly, the qualitative data is collected and analyzed in forms of case studies and reports. Qualitative research examines and deals with non-numerical data like case studies, depth interviews, surveys, and observations. Indeed, the qualitative research aims to understand certain phenomenon based on the viewpoint of the participants, that leads to formulating in-depth knowledge in the area of research (Chesebro & Borisoff, 2007).

The context and quality of the research

Baxter and Jack (2008, p 2), the qualitative case study methodology enables researches to go beyond basics and analyze the complex individual or organizational phenomenon. Besides, the qualitative approach is used as explanatory research, aiming to explore new phenomenon using various sources of data. To go further and identify the research topic eligibility for the qualitative case study research methodology, Yin (2003) identified three main elements that should be met when applying the case study in the research topic:

- The scope of the study should be built around answering how and why questions. Relating to this condition:

  The focus of this thesis is to answer: How to link big data and business model thinking the healthcare context?
- The behavior of individuals or organizations involved in the study cannot be manipulated. Relating to this condition:

  The selection of the case study companies was based on their focus, that is mainly confined to the focus on the big data and providing solutions for the healthcare industry.
- Researchers should have separate conditions, and they believe they can be formulated within a contextual framework. Relating to this condition:

  The author believes in the possible links that will connect the big data concept with the ecosystemic business perspective. Then suggesting a platform for big data business models, based on the intersection of the common elements between the big data and ecosystemic business model characteristics

The validity of qualitative research refers to the appropriateness of the research tools by which the researcher uses to collect and analyze the research data (Leung, 2015). From this perspective, the validity of qualitative studies is divided into internal validity and external validity. The internal validity refers to the credibility of research findings, while the external validity refers to the transferability of the research findings. It means to what extent the research findings can be generalized to other contexts of research (Altheide & Johnson, 1994). The reliability of qualitative research refers to the replicability and repeatability of the research process. It reflects the consistency of the research results over time (Leung, 2015; Golafshani, 2003). The evaluation and quality of the research are discussed in detail in chapter 5.

3.2 Sampling, data collection and analysis method

This study uses the purposeful sampling technique in identifying and selecting the case companies for this research. As the purposeful sampling help the researcher to select knowledgeable individuals, groups or companies about the certain phenomenon to the topic of interest (Palinkas et al, 2015). The data in this research is collected using semi-structured interview methodology. DiCicco-Bloom and Crabtree (2006) argue; the semi-structured interviews are one of the common techniques in collecting the data for qualitative research. A list of pre-determined open-ended questions is formulated based on the scope of the research, in addition to the emerging questions that may evolve during the interview discussion. The setting for this methodology is usually determined in accordance with researcher and interviewee timetable, the duration ranges from 30 minutes to several hours. From this perspective, the interview questions consist of 26 questions in total (Appendix 1) were conducted based on the theoretical farmworker of this study, including the platform of business models. In order to be able to collect high-quality and representative data, the interview was divided into four parts:

First, the background questions to formulate an overall understanding of the company focus, organizational structure, marketing strategy, and the company tendency towards innovation. Second, the big data related questions to identify the role of data in the company's business operations and its related aspects like the management of data sources, the control of the data-oriented systems, the accessibility of the data and its related practices. Third, the ecosystemic business model part to collect data related to value creation and delivery from the ecosystemic notion. In addition, identifying the various perspectives of the business relationships; including systems integration and coordination for improving customer experience. Then, the platform of the big data business model is created based on the intersection of the common elements between the big data and ecosystemic business. we focused on collecting data related to the ownership concept, conflict of the business relationship, centralized control, modularity of the business models, and consistency of the business processes.

The structure of this research formulated around three major case studies focusing on the big data in the healthcare system, also they are working with the icory project consortium. We gave the letters (A), (B), and (C) to the case companies respectively. In terms of data collection, table (3) provides a summarized framework for the case companies, the company scope, the number of interviews, and the role of interviewees in the organization structure. Before conducting these interviews, an invitation was sent by email to participants, then the timing was scheduled within the working day hours to ensure the commitment factor. For companies located outside the city of Oulu region, we agreed to conduct the interview virtually through Skype. The interview discussions started with a brief description of the research scope; in terms of linking between the big data and the business model thinking, then discussing the aims and goals of participating in the icory project.

Table 3. Summary of the case companies

Case Companies			
Case	Company scope	Number of interviewees	Organizational role of the interviewees
A	Providing an AI model for the healthcare system, that makes predictions from the patient-generated data.	One 26/03/2019	Lead Architect
B	Providing multiple platforms for collecting and analyzing the medical information from various sources including hospitals, clinics, health centers, and patients.	One 29/03/2019	Chief Sales Officer
C	Connecting patients and hospitals digitally together through specialized care coordination platform.	One 02/04/2019	Chief Sales Officer

Method of analysis

This study follows the abductive research approach, it starts with the theoretical background to formulate a pre-understanding of the research phenomenon and guide researchers to read the empirical data. The understanding of existing theories changes while progressing in the analysis part (Lipscomb, 2012). The generation of research question in this study is done to narrow the scope of study and identify the possible links between big data and business models in the healthcare context. In order to answer the research question of *how to link big data and business models in the healthcare context?* The analysis of data is focused on identifying the common elements of value creation in the big data and business models. Then, identifying the main elements for the big data business models.

This study follows the content-based analysis or the thematic way of analysis. In this way, the qualitative data is coded into keywords to identify the common patterns included in the data. After identifying the main patterns of the study, the data should be classified to the related patterns to formulate a framework for the preliminary research results (Sgier, 2012). Further, the main patterns should include sub-sections for depending themes. This way helps researchers to classify the data into specific categories and components, in order to formulate a comprehensive understanding of the research phenomenon (Aronson, 1995). Following these steps, the researcher will be able to build a valid argument of his/her study with respect to the literature background, contrast new phenomenon and validate the previous research findings (Constas, 1992).

Relating to this study, the analysis process started with a transcription of the recorded interviews into the textual format, as all interviews were recorded after getting permission from each participant, this step is done to ensure all responses were included in the text. Further, we read them carefully and identify the main keywords with the response to the research framework. In this research, we did not use any software to code the keywords due to the small size of data. Based on the research framework introduced in chapter 2 based on the synthesis of the literature background (see figure 13), the data were grouped into three main categories. The first category is related to value creation in the ecosystemic business process. In terms of partnership in the ecosystemic data-oriented model, the accessibility of data and ownership aspects. The second group is related to the value creation in the data-intensive system (e. Healthcare industry) in terms of data monetization, data sharing, and EDI, and pathways to value creation in the data system. The third group was related to the centralized control of the data system and the modularity of the business model.

Afterward, some direct quotations from the interviews have been taken and included in the analysis part; to include the opinion of the interviewees in the analysis process. As Chesebro and Borisoff (2007) argued, qualitative research is basically done to understand certain phenomenon based on the viewpoint of the participants. Each interviewee was assigned two letters abbreviation to refer to them in the analysis part as follows (JH), (AM) and (ML) reflecting the case companies (A), (B) and (C) respectively. The empirical data is analyzed in chapter 4, then the findings and answer to research question are discussed in chapter 5.

4 DATA ANALYSIS AND FINDINGS

The aim of this study is to increase the understanding and build links between the big data and business model concept. In this chapter, we analyze the collected data to answer the research question "how to link the big data and business model in the healthcare context?". Then providing a complete framework for the big data business model in the healthcare system. The context of this chapter is a summary of case companies, dimensions for value creation in the ecosystemic healthcare context, dimensions of value creation in the data-intensive system (ex. Healthcare industry), and the modularity of the business model and value creation.

4.1 Summary of the case companies

As mentioned earlier, the main research question of this study tries to understand how to link between the big data and business models in the healthcare system. In order to reach this goal, the empirical study is formulated around three case major companies to collect research data, and then analyze these data to address the research goal as follows:

The case company (A) is a publicly registered software company that specializes in digital business solutions. It has a traditional organizational structure operating in the Nordic market. Their business operations focus on the retail business, e-commerce, and point of sale systems. Recently they started an incubator system which pushed their business operations towards the robotics industry, Artificial Intelligence (AI), and the healthcare system. Indeed, the company (A) is new to the healthcare system but they are using their experience from various industry in creating and delivering their values to the healthcare system. As mentioned by Mr. JH, company (A) is a big company, that operates within several ecosystems to capture the opportunity, and then create a business wherever the business opportunity is found.

> *"Of course, we are a part of different kinds of ecosystems that contain several partners and of course, we have bigger customers and bigger cases that need other bigger players to be involved in our business*

processes. So, case by case we utilize our network for subcontracting and so on. We are part of several ecosystems". (JH)

The company (A) is keen on getting its product into the healthcare system. Because healthcare is dramatically changing in the last few years, based on the rapid development of the AI and the research data gathered in the previous years. Accordingly, the healthcare system is something that will give for business investment in return.

"Regardless of the challenges that the healthcare imposes ranging from data privacy to strict roles and high consistency. But overall the overall healthcare system is durable, and we will have a lot of promises in the future". (JH)

The case company (B) is a Finnish company working in the Nordic region. The company basically specializes in the data system, mainly collecting and analyzing the medical information from various sources including hospitals, clinics, health centers, and patients. The company aims to change the traditional healthcare system in terms of medical information processing, support the healthcare professionals to establish reliable treatment options, and help patients to get convenient healthcare options. Accordingly, there are around 300 clinics are using company (B) system, that directly sends the data for the company's registers. The integration between the company's registers and system users -hospitals and patients- is the key to provide reliable insights for the healthcare practitioners and patients.

"(...) we have a solution called my health, which used by patients themselves. The register sends the messages to the patient, then the patient fills the forms and sends them back to our registers. On a larger scale, the hospitals are using our register, enabling us to pick the data from the data register and collect them together in the company database". (AM)

The case company (C) is a small Finnish registered company that is focusing its business processes in the healthcare sector. The company (C) is doing a care coordination platform for the hospital, mainly they are connecting the hospitals and patients digitally together. This coordinating system is done via a mobile application that is controlled by doctors and nurses. They communicate through the application as they get all information in forms of reminders and questionnaires. So, when the patient gets indications, she/he will go to the hospital and then the patient will have all care related information. The whole communication process between patient and hospitals, before and after the treatment is digitalized into a mobile application.

> *"Our scope is aligned with icory because we are aiming to digitalize the whole patient care system, before and after their encounter to the healthcare system". (ML)*

The company (C) is having a linear organization structure to enable innovation and meet growth requirements. However, the company is following a simple innovation strategy as there is a high interest from the healthcare system in their product, so they are evaluating customers feedback and requests, and then adding new features accordingly. The company platform is jointly codeveloped between 2016 – 2017 by the University of Oulu and the University of Helsinki. After that, the company continued collecting information from its customers; concerning what will be the next steps in their platform.

> *"(...) hospitals are evaluating our features and providing us with information with what they want to add to the platform". (ML)*

Depending on how many requests they get from several hospitals concerning certain features, the product managers evaluate all requests they get. Later, they decide on which feature that will be added to their platform. The decision is taken based on the number of hospitals who requested these features. The company is not taking any part of the innovations sponsored by the Finnish system like OuluHeath or DigitalHub. However, they are independently improving their platform by themselves.

"In icory, we want to have knowledge about how to collect the data and what kind of data is important for the nurses and doctors. we are interested in the anonymous data because we do not want to know which patient is using the application, then with these kinds of data we try to improve our platform". (ML)

4.2 Dimensions for value creation in the ecosystemic healthcare context

"From the ecosystemic business perspective, no single company can have an overall knowledge about the end customer" (Weill & Woerner, 2010)

The ecosystemic business formulates relationships with industry partners, as it provides the dynamic capability for the company to explore the business opportunity and value capture and creation (Gomes et al, 2018). Yet, business organizations should utilize their dynamic capabilities to create their competitive advantage and deliver superior customer experience for their customers. The stakeholders in the ecosystemic platforms include governmental organizations, profitable and non-profitable business partners, universities, and research projects.

"Data sharing means that we can pick up data files and send those for different kind of vendors like the ministry of healthcare, and of course, if we are having partners, we share these data. Also, if we have a deal with a hospital district, we make all data sharing in cooperation with the hospital district". (AM)

The ecosystemic business process meant to be an enabler for different business actors from various fields to get together, then cooperating to create an efficient business process and give extra values for their customers. Further, it means expanding the business scope into new areas, that the business was not penetrating before.

"The integration of our system with other systems enables the continuity of our business, as without integration; we cannot have any business at all". (JH)

> *"There are certain features that our customers are requesting from us like medical video visits. And it does not make any sense to build our own one, because there are successful operators doing these solutions. So, knowing the right company/partner is very beneficial to cooperate and add the feature to our platform". (ML)*

The data generated from the icory as a research project is helping the project consortium to develop solutions for preventive healthcare by getting access to hospital generated data, healthcare centers, and researchers. On the other hand, the partnership may lead to certain types of conflict over the ownership of data source or evenly controlling the system.

> *"In some cases, other parties if they find that there is a profitable business that we do, then they try to do the same that we do though. Kind of copying our doing, in some case that thing has happened, and it was the worst thing to happen. We protect it with contracts and securing our products with our IPRs". (JH)*

4.2.1 Platform for partnership

Ecosystemic business context provides a platform for the business participants to cooperate, interact and participate in the value creation process. The high interdependency between system actors opens the pathways for the system actors to get complete knowledge about the end customer and build a long-lasting relationship with the end customers. Yet, companies cannot have a piece of complete knowledge about the end customer, in terms of what they need and how they evaluate the business offering. Thus, the integration between system partners provides complementary support for every company included in the platform (Weill & Woerner, 2015).

> *"(...) we cooperate with hospitals to get knowledge about the patients and provide our care coordination platform, where patients are following some steps to fill their data and define what is necessary for their treatment". (ML)*

Partnership and integration between system actors within the ecosystemic context work as an enabler for innovation. It guarantees the continuity of the business process. For example, the AI-based systems need massive amounts of data behind it, that cannot be obtained without having several partners from various industries. From this perspective, the company (A) is having several business models that correspond to different industry/or business field.

> *"(...) in many cases, our partners provide us with the needed part to get into the customer whether it is analytics, hardware or similar. So, we can get our software for the customers. I would say that the ecosystem works like that, with the help of other parties, we can create values for the customers. I would say the ecosystem works as a complementary system for our business process". (JH)*

However, the integration between system actors in the data-oriented systems involves centralized control over the database system. The planning and control of the overall system are granted to the system owner as a residual right of control (Grossman & Hart, 1986). Hence the system owner is having control over the data repository, it allows the system owner to maintain the flow of the in/out data to guarantee high quality for the data analytics. The centralized control over data system provides system actors with reliable data that improve the decision-making process (Ramamurthy & Premkumar, 1995).

> *"Of course, we need to have a partnership with the hospital to evaluate what we need for our platform. So, we need to have a very close partnership with hospitals and identifying what kind of feedback we need to get, in order to improve our system". (ML)*

> *"(...) ultimately doctors and nurses will be able to track the patient health condition, compare treatment options, and identify the best treatment options". (AM)*

No company can have the full knowledge about certain customer/market, the cooperation between industry partners "ex. hospitals and system providers" enables the data-oriented systems to easily integrate and get access to the specific market/industry. Indeed, business organizations are forced to get external help in the customer knowledge side, which is defined by Weill and Woerner (2015) as the plug-and-play model.

> *"(...) with the icory consortium, we can get access to the foreign market. Ex. University hospitals in Singapore". (JH)*

> *"The partnership enables to strengthen our overall business strategy, it enables us to get access for the market". (AM)*

> *"Our partnership with General Electric enables us to reach hospitals that want to integrate our platforms to their General Electric system". (ML)*

Overall, the integration between internal and external system actors enables the sustainability of resource use. It means making the best use of the resource until the end of its lifetime. In the digital business context; it allows companies to expand their business process with a lower initial investment cost and minimize the risk level. Further, the integration of capabilities enables the expansion of the business process into foreign markets.

> *"The integration can happen by defining our process at the beginning, then coming to our software. In practice, we give them access to our API to enable users to get access for the functions they need". (JH)*

4.2.2 Access rather than ownership

In the context of the healthcare system, the company (A) is using the AIaaS model to corporate with the industry partners. The AIaaS model is a third-party offering of the artificial intelligence shared platform with industry partners. It is allowing system actors to get involved in the process without considering a larger investment. In the AIaaS model, the customer generated data goes through the system – data input –

and the system algorithms go through the data, and then the results are generated in forms of insights for the company and predictions to the end customer.

> *"Prediction from the data source and of course the outcome of the AIaaS model is defined with the customer on what they want from the data and we try to get it as good as possible. Probably in sometimes the predictions are not so good as it all about data, it depends on how many lines of data we have and what kind of data and the level of difficulty to go through the data, either it is structured data or unstructured data. So, in short, we mainly give predictions from customer data". (JH)*

The consistency and efficiency of the business process are defined from various aspects related to the analytics of data, ownership of the data, and customer values. However, the consistency in the data-intensive systems means to maintain the high level of accuracy in the data analytics, that guarantee the continuity and transparency of the business process (Iacovou et al, 1995).

> *" We have centralized control over our data; because in our solution we are on the top of the pyramid, so we can decide who can use this data and on which project we can go on". (AM)*

> *"We started the system from scratch, so we are the owners". (ML)*

The control in the data-oriented system starts with defining the type of control the company should have, either control the ownership of the data sources or the analytics and data insights. In the ecosystemic context, the modularity of the system enables the platform owner to grant a certain type of control for the system users. This control is related to optimizing the platform content in accordance with business needs. The modularity of the platform helps the business organizations to expand their business scope and operate in the foreign market.

> *"Hospitals can use our platform to optimize their content, they do not have full control over the platform. Otherwise, they will have an empty platform to control what they want". (ML)*

> *"(...) at the point, we do not have any sharing strategy with our partner. But we grant access to other partners. The AI service is a system combined of many open sources". (JH)*

4.3 Dimensions of value creation in the data-intensive system (ex. Healthcare industry)

"When it comes to human lives, profits should be the main motivation for the healthcare industry" (Raghupathi & Raghupathi, 2014)

Based on the discussion in the theoretical background, the concept of big data is related to the development of information technology and artificial intelligence. The big data is defined by the enormous amounts of data generated over time. From the technical point of view, some open source software like Hadoop works as a distributed processing system between all system actors. It processes the data and stores its applications in forms of the clustered system, that provides a reliable source for information in the decision-making process.

> *"Our system is working at the University of Oulu hospital and collecting data from the patient records, laboratory systems and a lot of many other data sources. We are integrating our system with hospitals and collecting data in our system, which is called disease-specific registers". (AM)*

The data-oriented systems should have the ability to collect, analyze, and then monetize the generated data among all data sources. This is should be done through an ecosystemic business perspective, it guarantees continuous communication between system actors; to analyze the huge volumes of data and get meaningful insights.

"The big data is defined as the data lack where all data is gathered and stored and from the technical purpose, it means Hadoop. We use open source software to process our data and provide meaningful insights for our customers" (JH)

4.3.1 Data monetization and ownership

In the field of information technology, computers are used to process different kinds of information and provide meaningful insights, whilst artificial intelligence relates to the machines ability to imitate human's behavior. The value creation of the data-oriented systems starts with the data monetization (Perler, 2013). The monetization of the data converts the intangible values of data into a competitive advantage for the business organization. In the healthcare system, hospitals anonymized patient data to comply with the security standards, so the identity of patients cannot be revealed. Afterward, the patient data is monetized with the business partners "system providers" to improve the usability of the system, add/remove certain features to comply with the healthcare standards.

"There are certain things that hospitals can do, and other things hospitals cannot do. So, hospitals are not hard-coding the system, but they are providing us with the anonymous patient data to improve our system". (ML)

"Our model works hand-in-hand with the healthcare system, so when our partners "means hospitals" gives us the data, we give back the mode; then we create better service for our customers". (JH)

The privacy and anonymization of the data in the healthcare system considered to be one of the hardest parts of the ecosystem. Because the data will be exchanged from patient records to the company platform, then it may go from one company platform to another company platform and so on. So, data anonymization takes some time to finalize the contracts and complying with the rules governing these aspects, which makes it a time-consuming ecosystem.

Based on this, there are three pathways for companies to monetize their data, the first pathway requires the company as a system owner to take the high risk and monetize their data by developing their technical and analytical capacity at the same time, which requires higher investment cost and it promises with higher returns. The other two pathways suggest developing the technical capacity first or obtaining the technical infrastructure before having the technical capacity (Najjar and Kettinger, 2013).

> *"Hospitals are using our registers, enabling us to pick the data from the data register and collect them together in the company database". (AM)*

> *"Our application collects the data from patients themselves, as they fill-up some questions in the applications, then we show it in a simple way to be understood by doctors and nurses". (ML)*

The optimization of the service cost in the healthcare sector is not a priority for the healthcare industry. Instead, the priority is to give the patients a convenient experience. Because normally they are worried about their health status and there is no way to bring additional pressure for the patients. Accordingly, the healthcare (as data owner) monetizes the anonymous patient data with their business partners/ system providers to get insights from data and improve the caring system. The big data is able to transform the healthcare sector and drive some business values out of it.

> *"Hospitals get access for the results as it gives predictions from the data that it goes through and update the system, so they can improve their services based on these predictions". (JH)*

4.3.2 Data sharing and Electronic Data Interchange

The data interchange between business actors happens by integrating the organization internal elements "including the functional and technical capabilities" with the suppliers and other trading partners elements. This guarantees the faster transmission of information between ecosystem actors, higher quality and accuracy of the collected data because the human factor is replaced by computer-to-computer or terminal-to-terminal system. The benchmarking system in the case (B) and AIaaS in the case (A) are having the same scope in helping patients to get the better preventive healthcare experience, while at the same time they are making some business values out of it.

> *"(...) we make stories about the patient situation in different ways, the system includes different kinds of users like patients, physicians and nurses. The generated data includes patient records, laboratory systems, prescribed medicines and lots of many other data sources. We are integrating our system with hospitals and healthcare centers to collect data in our system which is called disease-specific registers". (AM)*

Currently, when the hospitals are inviting patients to the operation/surgery, they do most of the tasks either by calling the patients and asking them some questions or sending some papers by emails asking certain questions to be filled out. The data-oriented solutions enable hospitals to invite patients to download the application, and then they can find all relevant information. The purpose is to decrease the amount of manual work from the nurses, decreases the number of phone calls, and decreases the paperwork. Then the patient is better informed with the treatment procedures, while on the other side, the doctors and nurses are earlier informed about the patient status. In some cases, patients may have some problems to prepare himself/herself for the operation, so doctors and nurses can notice that before.

> *"Hospitals provide us with data, then they get insights and predictions from this data. And hopefully, we get some money out of it". (JH)*

The interchange of the data between system partners provides healthcare system and business organizations with the capacity to analyze patient behavior before and after the treatment journey. The healthcare system imposes lots of procedures in case of medical operations and surgeries. It is crucial for the system to improve their procedures, provide patients with better treatment options.

> *"We aim to lead the digitalization of healthcare system and help doctors and nurses to save time in the outpatient care" (ML)*

It is obvious that data is controlling the business operations and value creation in recent decades. The profitability and market promise of the business opportunity can be defined by the level of data that the company owns and the quality of its analytics (Chen et al, 2012). In the case (A), they are trying to use customer-generated data, then analyze them to gain useful insights and develop their system accordingly. In this case, they are creating solutions for the healthcare system in general and end users -patients-. These huge amounts of customer-generated data is helping the company to give extra values for the customers compared to the current services they currently have, says Mr. JH.

> *" (...) our registers cover almost 60 disease types that are planned to improve the caring system and provide the best treatment options for our patients. All our registers (time-based registers) can automatically send different questionnaires to patients, which help the medical system to get the patient data records". (AM)*

4.3.3 Pathways for value creation

Therefore, the value creation and delivery in the data-oriented system is done through four dimensions: business-related value, scientific value, community value, and individual value (Tempini, 2017):

Business value: it can be created when the data gives meaningful insights to go through the commercial research process. In this case, the generated data should support the creation of the commercial value, whilst it aims to develop a new solution/product for the customers. In the healthcare context, the insights from data analytics usually come from different sources like patient-generated data, hospital generated data and so on. Taking icory as an example, it gives companies the opportunity to get connected with hospitals, patients, and doctors.

> *"The big data enabled our company to get involved in the healthcare business. Regardless of all the strict requirements of the healthcare system which we have to comply with, the data enables us to get connected to hospitals, health centers, clinics, doctors, and nurses" (JH)*

Scientific value: exists when the data gives insights for conducting scientific research. The recent data generated in the healthcare sector for the case companies in the icory project gives these companies the likelihood to conduct some research in the predictive healthcare system. Because the healthcare data-oriented models help companies to create some predictions from the patient-generated data including medical imaging, laboratory reports, physicians reports and prescriptions, and even information about medications.

> *"(...) that is why we are also doing the icory research; because there are lots of motivated researchers who provide us with useful information to develop and update our platform". (ML)*

It can be challenging to identify all reliable data sources in this early phase of research; because some systems like the benchmarking system used by case company (B) contains data generated from the patients themselves and it might include human errors in some cases. However, these companies are building their data algorisms to collect data from different data sources, and then help the end customers (patients) to get better preventive healthcare experience. In the meantime, it provides physicians and nurses with the decision support system like giving them a second opinion.

Community value: value is created when the data is used on a larger scale to expect some societal phenomenon. Ex. In the healthcare context, it helps companies to identify the representative data sources to study certain population, then some predictions are made based on the data sources. Then the outcomes are directly used in the preventive medical systems, like mandatory vaccinations before traveling for certain geographical areas. Indeed, it helps humans from exposure to certain hazards that may impact their lives.

> *" (....) if we will be able to get access to the normal patient history records, so we can create some predictions out of it based on larger data that goes through like population in different locations, matching some rules for AIDS, Hepatitis and smoking, etc. we are building those algorithms at the moments and collecting those data points". (JH)*

Individual value: system generates tangible values for the end customers. Hence, the value is created when customers get the outcomes of the system, that can be in the form of application systems or any other forms. In the healthcare context, the end customers (patients) get personalized values through preventive healthcare solutions. In this approach, companies should track the usability level of their offerings to main/improve the level of individual value; in terms of how the system is used, what are the parts that are mostly used, and what is the customer feedback.

> *"We are interested to get data related to our healthcare dashboard. In another way, we are interested to know how our healthcare professional dashboard is used, how the nurses and doctors are using the platform and how we improve it" (ML)*

4.4 The modularity of the business model and value creation

The modular producer model enables the business organization to survive in the competitive market, evenly if there are many other producers offering some kinds of similar offers (Weill & Woerner, 2015). It reduces the complexity of the business process and decreases the level of intense competition. The modular business model enables business organizations to rapidly adapt to customer requirements; in terms of enhancing the innovation of the business process and orienting the overall business concept based on the end customer requirements.

> *"Our approach is to build a modular platform and give our platform for the hospitals to guide our patients. It does not matter if it is for ear diseases, nose diseases, and so on. Every patient can use our platform by defining their own treatment process in our platforms, that enables*

us to collect the necessary data to guide the patients to hospitals and then from hospitals to home". (ML)

From this perspective, the producer should grant a certain level of limited control over the product/platform for their partners, enabling them to customize the platform in accordance with their needs.

"(...) hospitals do not control our system, but we give access to our Application Program Interface (API), where they can get access to the stuff they need". (JH)

"It is not possible to have any closed system, because it is the customer data and we only own the algorithms, so we give hospitals the accessibility to guarantee the consistency of our business". (AM)

The modularity of help information technology companies in the healthcare system to cooperate with hospitals; in order to identify what they need to form their platforms. Indeed, without a partnership with hospitals, business organizations will not be able to identify the right way of applying their new technologies. Thus, hospitals evaluate the platforms and their features, then they send back information for the IT companies to update/modify their healthcare solutions.

"Basically, we have to develop our registers all the time based on the feedback we get from doctors and doctors, so our customers are not controlling the data, but we are doing cooperation with our customers. They are the producers of data, and they need money out of that. so if we do not have a good relationship with customers, we will not have the data". (AM)

In the big data context, the profitability of the business opportunity is determined by the level of owned data and its analytics in the business context (Chen et al, 2012). In the healthcare context, hospitals have the legal right to own and anonymize patient data to ensure the privacy and security of patient information. However, these data will not provide any indications for the hospitals if it is not analyzed in a certain way, to provide doctors and nurses with insights about the patient treatment status. So, the partnership between the data source (Hospitals) and platform owners (business organizations) is done to enable the data exchange and system integration between hospitals as a source of data, and platform owners as providers of data insights.

5 CONCLUSION

This chapter provides an overall discussion for the empirical findings and answers the research question. Then, theoretical conclusion, managerial implications, limitations and evaluation of research, and recommendation for future research.

5.1 Discussion of the empirical findings and answer to the research question

The main aim of this study was to increase the understanding of the big data business models in the healthcare system. The progress of this study added understanding of modularity platforms and how they can be applied in the ecosystemic models. Further, the study provided a profound for how the ecosystemic actors coordinate to improve customer experience in the healthcare system. The theoretical framework was divided into two parts: the first part summarized the existing theories about the big data and its impact in the healthcare system, while the second part emphasized on the business models and ecosystemic business in the digitalized context. Based on the existing knowledge in these parts, the research framework (see figure 13) was formulated to link between the big data and business model. The empirical study was aligned with the theoretical framework alongside the research process. Further, it highlighted new aspects for the study, that is presented in the figure (15).

The common elements between the big data and business models were identified and examined in the empirical analysis. Further, it was found that the modularity of the business process is the key success of the big data business model. This study validates that the modularity in the business is the key concept for value creation in the data-oriented business (Weill & Woerner, 2015). In terms of providing consistent and innovative business process (Lim et al, 2017; Gomes et al, 2018), ability to adapt to various ecosystems to maintain the rivalry power (Wirtz et al, 2010), and activate the element of customer centricity to ensure they get the most convenient experience. (Tempini, 2017). Accordingly, we suggest that the ecosystem should use the customer as a centric point for the ecosystem. Then, customers will have the possibility to choose what they want from the overall ecosystem. This requires ecosystem actors to have a certain degree of modularity, where they grant system users to have partial control over the data-oriented platforms. It enhances the process of value creation and helps in expanding the business scope to foreign markets.

Response to the research question

How to link the big data and business model in the healthcare system?

From this context, the answer to the main research question is, the link between big data and business models is done by adapting the modular-ecosystemic platforms in the big data business model. The ecosystem should be a customer-centric ecosystem, that puts the customer as a focal point of designing the overall business process. The answer to this question is divided into two parts; the first part is to adopt a platform for partnership with the ecosystem actors. While the second parts add modularity to the business ecosystem. A detailed description of this aspect will be explained in the following sub-chapters.

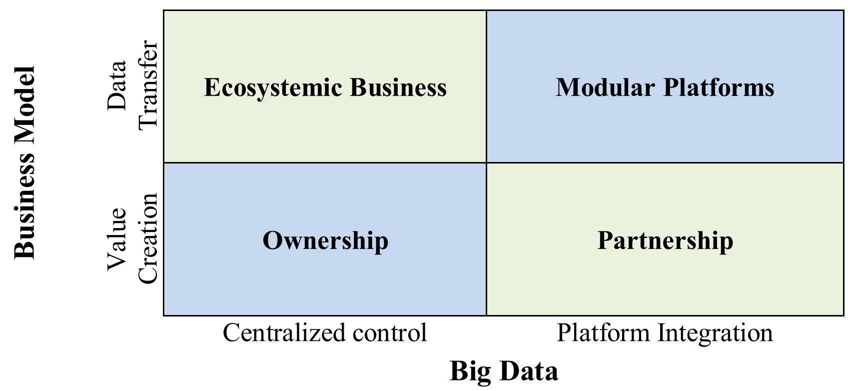

Figure 15. The platform for the big data business models

To support this answer, the platform for big data business models is presented in (Figure 15). The empirical evidence from this study indirectly confirmed the findings of Van et al, (1995); when it comes to the big data context, the issue of centralized control over data sources, right to code the system and data sharing and integrations play the dominant role in determining the notion of the business relationship with other business players. While from the ecosystemic business model perspective, the empirical evidence directly confirms the findings of (Iivari et al, 2016; Gomes et al,

2017) related to the formation of the ecosystemic business process and integration between system actors. It is mainly done to speed information transfer between system actors, create and deliver values to customers, and ensure the great customer experience. Thus, the links between big data and business model thinking are done by identifying the four major platforms (Figure 15). These platforms are a platform for ownership for the data-oriented platform, a platform for modular business process, a platform for ecosystemic business, and a platform for partnership. An explanation for these platforms is provided in the following subchapter.

Further, this study identifies two approaches to create value, commercialize the data-oriented platforms and comply with the requirements of various revenue models as follows:

A platform for partnership through Partnering with the data source like hospitals and medical centers because they have the responsibility of collecting patient data, guiding patients on how to use the platforms, then providing platform owners with feedback (Raghupathi & Raghupathi, 2014). The feedback usually includes suggestions for improving the platform usability and requests for new features/or optimization of a certain feature. It is related to Wirtz et al. (2010) findings on the strategic development of the business models in digital settings. Wirtz et al. (2010) study suggested four typologies for the business models related to the content, commerce, context, and connection. The findings of this research go hand in hand with the content-oriented business models, as the platform should comply with the end users -patients- requirements. Moreover, the platform should be based on a user-friendly interface. Otherwise, the patients will complain about its usability to the corresponding hospitals.

Ecosystemic context and modular business process as the platform operators do not have complete knowledge about the end customer, so the integration with hospitals is the key success factor for their business. As mentioned in the data analysis in chapter 4; without hospitals, the big data firms cannot identify the right direction of commercializing their platforms. This concept complements the prior study conducted by Weill and Woerner (2015) and Wirtz et al, (2010) to identify the types of business models in the digitalized business environment. The four types identified by Weill and Woerner (2015) were discussed earlier in chapter 2 to identify the differences between the supplier model, the omnichannel model, the ecosystem driver model, and the modular producer model. Overall, the main argument of this study provides a novel way to the modularity in the big data business models, which enables the system customers to control the system. Further, it will give the possibility to end customers to choose what they need from the overall ecosystem offering. Neither of the case companies is applying the modularity on a larger scale. However, they are willing to apply modular platforms when growing to foreign markets.

5.2 Theoretical contribution

This study introduces a novel way of identifying the big data business models in the healthcare context and it provides a contribution to the existing literature from several aspects. The study began with understanding the big data systems and how value is created in the data-oriented system. Further, a connection with the ecosystemic business models was conducted to identify the common links between the big data and business models, which led to identifying the platform of big data business model in the healthcare context.

To begin with, most of the existing literature used the same research approach to examine the process of value creation in the healthcare industry as a data-oriented system. Raghupathi and Raghupathi (2014) study examined the potential driven benefits from the big data analytics in healthcare, while Tempini (2017) study identified nine pathways for value creation in the data-intensive systems. On the other hand, some studies examined the business models in digital settings and value creation in the data-intensive systems (Wirtz et al, 2010; Iivari et al, 2016; Pateli, 2003). However, the existing literature has not proved yet how different business models can be aligned to work together in the data-oriented systems; especially when it comes to the healthcare context as a data-driven system.

This study agrees with the suggestions from previous research to identify new platforms for the ecosystemic oriented business models, as an element to comply with the requirements of value creation in the big data and AI fields (Tempini, 2017;

Gomes et al, 2018). We connected the common elements between big data and ecosystemic business to propose the model of this study. From this aspect, we realized that healthcare data is not the main priority of the companies doing their businesses around the healthcare system. They are mainly concerned about the usability of their solution, shifting out the responsibility of data collection, quality, and reliability of the data to the healthcare system including doctors, nurses, and the overall hospital systems. This finding supports the previous studies conducted by Raghupathi and Raghupathi (2014) and Jeble et al, (2018) that suggests a framework for big data analytics in the healthcare sector; as hospitals are the main contributor to this quality. From this viewpoint, operators in the healthcare system should understand every aspect of the collected data in terms of what patients are saying, how the data is compatible with diagnoses, and how patients interact with digitalized data platforms. This responsibility comes as a compulsory element for the healthcare system; as a result of the laws governing the privacy and safety of the patient's personal information. Consequently, hospitals have to collect patient data using data-oriented solutions, then anonymize the data before exchanging it with business partners.

An earlier study conducted by Raghupathi and Raghupathi (2014) proved; the data-oriented platforms are specifically designed to collect and analyze data using special tools like Hadoop, and then provide useful insights from these large datasets using special programming models. These analytics in the healthcare context can improve the diagnoses process, minimize waiting times especially in the public healthcare systems, and support doctors and nurses to take a well-informed decision. Because these insights represent kind of the second opinion for the healthcare professionals, while it helps patients to actively track their treatment process. However, there was no clue for identifying a common platform for the data-integrated solution. This study confirms Raghupathi and Raghupathi (2014) findings. Further, it provides empirical evidence for the process of value creation in the healthcare context by identifying a platform for big data business model, that is based on the value creation in the data-intensive systems. The following subchapters provide an explanation for this finding.

5.2.1 Ownership and modularity of the data platforms

The evidence from empirical study directly confirms the findings of a prior study done by Grossman and Hart (1986); in terms of the centralized residual right of control, which enables the central business organization to distribute and grant the standardized system access through internet-based applications. This was approved by (Van et al, 1995) study, as centralized control gives the residual right of control to the system owner, so they grant the full/partial standardized access to system users. From the technical point of view, storing data in a centralized repository allows better control over the ongoing and outgoing data, and helps in maintaining the same level of consistency over the whole business process (Grossman & Hart, 1986; Ramamurthy & Premkumar, 1995). But neither of these studies open the pathways for system flexibility and customization based on customer requirements. According to the empirical findings of this study, system owners can grant standardized accessibility for its customer but also they can request some minor customizations. This strategy is being applied by the case company (C) on a smaller scale, as they are still in the trial phase. But as mentioned earlier, it becomes necessary to grant system users the partial right of control when they have a wider customer base.

To support the justification of this finding (see figure 16), the data should be monetized to transform the intangible value of data into useful insights and predictions. The system users (ex. hospitals) have the bargaining power in terms of knowledge about the end customer (ex. patients). Therefore, the cooperation between system actors enables system owners to build a modular platform to maintain the efficiency of the business process. The study confirms the findings of Weill and Woerner (2015) related to modular business models. As the modularity is enhanced due to the little knowledge about the end-customers that business organizations usually have. This pushes the business organization towards getting external help in the knowledge side because they need to know more about the end customer, and then design their system accordingly. The study also supports the study of Wirtz et al. (2010) of adopting a customer-centric approach in business process, that puts the customer as a focal point of the company strategy, and then design the business process accordingly.

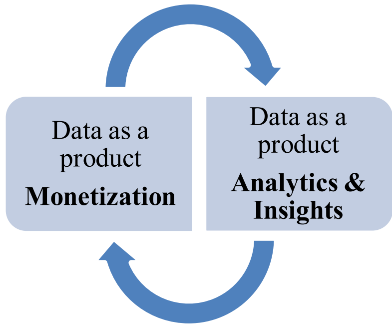

Figure 16. Collaboration and value creation in the big data business models

The computer-to-computer systems opened the pathways for business organizations to invest in the medical sector and obtain the capacity for monetizing medical data (Woerner & Wixom, 2015). Aforementioned, companies develop their systems to get the patient data from hospitals, process, and analyze this data. Then, provide hospitals with insights from this data. Najjar and Kettinger (2013) study provided three pathways for monetizing the data in the data-oriented systems. The first pathway requires a higher level of risk to be taken by the business organization to develop their technical and analytical capabilities at the same time. The other two pathways guide companies to either develop the technical capabilities or the analytical capability first, then complement the other part. The findings from the empirical study on the major case companies directly support the first approach of the data monetization in the healthcare context.

The findings of Weill and Woerner (2015) imply to the modularity of the business models, but there was not a clear clarification for the role of control in the modular platforms. The findings of this study agree with the modularity of the business process and suggest further implication for the modularity when it comes to the practice. In the healthcare context, the big data model works hand-in-hand between system owners and hospitals, because the user needs change over time and the system should correspond to these needs. The integration in the modular system provides system users with the partial right of control over the system. Yet, the system users cannot control the whole system. Otherwise, they will have an empty data-based platform to control. The user partial control in the data models should be placed with regard to the area of specialty. In the healthcare system, the platform providers usually have full control over the whole system, while users can change their content based on patient preferences, or physicians needs. In some cases, doctors are interested to know some aspects of the patient history related to a certain disease or tracking the patient recovery process. Accordingly, hospitals should have partial control to change/edit their own content based on customer “patient” needs.

Further, the study confirms that the control in modular business platforms should similarly work like WordPress for example, where users can change their content and design their final layout. This is related to the value creation in the data-oriented system, where the adoption of new platforms is required to ensure customers get the promised value and positively impact the decision-making process (Lim et al, 2018; Jeble et al, 2018). Accordingly, this study validates that big data platforms should be tailored to comply with the end customer requirements. The data business model does not allow system users to have the accessibility to the coding process (Jeble et al, 2018), they will have access to change the layout of the data. Otherwise, there will be some conflict over the whole system. From the business-wise, system owners should have the overall control to guarantee the continuity of their business process.

5.2.2 Ecosystemic business and partnership

The ecosystem of an inter-dependent network of actors contributes to the consistency and efficiency of the business process. In terms of identifying new market opportunities and creating values (Osterwalder et al, 2015). From the notion of the big data business model, the findings indicate; the ecosystem usually includes many partners where each member tries to sell their solutions for each other. In terms of the data-oriented systems, the companies exchange their customer data with other partners to get the insights in return. But every actor in the network needs to have a revenue out of this context. In this case, if there are many companies involved in providing the solution “system/or data insights”, the overall price will be extensively high for the end customer.

When it comes to data-oriented businesses, the analysis of customer-generated data helps companies to formulate a better understanding of customer behavior (Lim et al, 2017). Also, it provides the company with the pathways of creating new values, generating a new revenue stream, and broaden the based of its loyal customers. But customers need to have the freedom of choice in terms of what they need and what they do not need (Wirtz et al, 2010). This study confirms the concept of customer-centric business process and supports the previous views of Lim et al. (2017) and Wirtz et al. (2012). However, the empirical findings provide evidence that the business ecosystem needs to work based on customer selection. Companies can operate to provide varieties of features in the platforms, then the customer can have the option to select what feature they would need from the whole ecosystem. Accordingly, companies operate to provide varieties of features in their data-oriented platforms, and then the customer will have the option to select what feature they would need from the ecosystem. Otherwise, the system will not be able to function effectively, because every single company has its own profit strategy, aiming to achieve a certain target of product sales. The data-oriented businesses should give the flexibility to customers to select/include what they need from the data-oriented features.

The findings from the empirical study support the findings of Gomes et al. (2017) of adapting innovative ecosystems for improving the overall quality of the healthcare sector. This study goes further and identifies that; all system actors "in the data-oriented ecosystems" should work individually and together at the same time, then the customer will have the right to select what kind of features they want from these processes. Every part of the ecosystem needs to have control over their features; because it is finally depending on customer requirements and what they need. Thus, the ecosystem needs to be based on enabling customers to choose what kind of product they want to buy. For example, if the ecosystemic platform provides a variety of options to customers, that may include A, B, C, D, and E features to a data-oriented platform. So, if customers only choose to include the A and C features, then the ecosystem should provide customers with that. This also helps ecosystem actors to grow in the foreign markets based on the concept; customers do not have to buy all solutions from the ecosystem, the system should be very flexible.

As proven by earlier studies, the ecosystemic business should be designed to capture the values from technological innovations (Teece, 2010; Gomes et al, 2017). However, this study identifies a major challenge in the ecosystem context. Like every company in the system may have its own goals and market interests, and then every participant needs to have a promising revenue stream and sales target out of it. Putting these challenges together, the hardest part is to be committed within the ecosystem. Companies should define their goals from the ecosystem, then agree on which business plan to be followed for achieving goals. Indeed, the business plan could be the hardest challenge, not the integration itself. As it identifies how the ecosystem is going to sell its solution. For example, if company A is getting revenues of around 10 million from their part, company B may get only 5 million and company C may get only 3 million. So, each company should clearly define their business plan, revenue model before entering the ecosystem. All challenges must be solved before issuing new customer agreement, that will give the customer the possibility to select various features from the data-oriented platforms.

Summary

The empirical evidence of this study agrees with the findings of Weill and Woerner (2015) related to the adoption of the modular-producer business model. It enables the business organization to adapt to a variety of ecosystem. However, there was no clue about how to align different combines with different plans in the ecosystem. Further, this study disagrees with Van et al. (1995) and Grossman and Hart (1986) studies related to the ownership and centralized control over the data. These studies claimed that centralized control allows better control over the data and maintain the same level of quality over the system. But these studies did not clarify how centralized control is impacting the value creation process. Therefore, the empirical findings of this study validate the findings of Weill and Woerner (2015) related to the adoption of the modular-producer model. Additionally, we identified the modular platform for the data-oriented systems. In this platform, the centralized control over the platform is replaced by the partial control, where the platform users will have the right to control over their platforms. This is known as the Modular platform (see figure 17). The element of the value creation is applied in the modular platform, as the users will have the possibility to design the final layout of the platform based on the end user requirements. On the other hand, it enhances the value and practicality of the well-informed decision-making process (Lim et al, 2018).

Further, we agree with the study of Wirtz et al. (2010) and Iivari et al. (2016) from the shift of being involved within a value chain of a bigger company and provide a price-oriented offering for the end customer to the ecosystemic business. The empirical evidence agrees with the concept of a customer-centric business process (Lime et al, 2017). This finding suggests putting the customer as a focal point for designing the overall business process. However, we suggest that the ecosystem should be based on the customer selection. This requires all actors involved in the ecosystem to align their strategies together, as each company has different revenue models and different profit strategies. However, the integration between ecosystem actors will allow each company to have broader accessibility of the market and enable the customer to get a cost-efficient service.

Ecosystemic business model (Adapted from table 2)	**Consistency and Efficiency to the Business Process**	**Modular Platform**	Minimize Transmission Lifecycle	Minimize Performance Gaps	**A platform for Big Data Business Models**
	Integration Between System Actors	**Customer-Centric Ecosystem**	Value-Based Channel Relationship	Sustainable Business Process	Minimize Performance Gaps
	Speed in Information Transfer	Standardized Accessibility	Low Operating Cost	Cost-Efficient Service Offering	Innovative Business Processes
	A platform for Value Capture and Creation	**Customer-Centric Ecosystem**	**Modular Platform**	Value-Based Channel Relationship	Superior Customer Experience
		Centralized Control	**Platform for Sharing**	**High Level of Integration**	**Consistency and Efficiency to the Business Process**
	Big Data (Adapted from table 1)				

Figure 17. Updated framework for the big data business models

Figure 17 provides an updated framework for the big data business model. It validates the findings driven by the research framework (see figure 13, chapter 2).

Figure 13 was formulated based on the intersection of the vertical elements “major characteristics of the big data” with the horizontal elements “major characteristics of the ecosystemic business models”. The intersection between all of these elements was identified and labeled as described in chapter 2 (see page 56-58) while there were four elements that have not been identified; as we did not find enough evidence from the existing literature to validate this aspect. Accordingly, this study validates these aspects and identifies the modular platform for the big data business models and build the overall business ecosystem based on customer requirements.

5.3 Managerial implications

The results of this research were based on three case companies operating to provide data-oriented solutions for the Finnish and foreign healthcare systems. The overall scope of these companies was mainly focused on the Finnish healthcare system. The platform for big data business model as an overall finding of this research may help the business organizations involved in the big data industry to identify certain approaches for value creation and customer satisfaction. Moreover, it may help the organization to re-build their business models and develop their capacities to meet customer and market requirements.

The findings of this study related to the modularity and control in the data platforms may help decision-makers to realize on which kind of things they want to have control over the data platforms, and what kind of control should be granted to the system users. Because we found the centralized control over the data platform may lead to conflict between platform owner and user. Accordingly, a coordination platform may be the optimal strategy in the data-oriented system, where certain control will be granted to system users to give users the likelihood to control/optimize their content.

The organizations involved within an ecosystemic business context can adopt various strategies to coordinate, create and deliver values to the end customers. From this perspective, each organization involved in the ecosystem should clearly define their business model in terms of revenues and value creation. The ecosystem should be designed to give customers the flexibility of choice. The customer should have the ability to select what they want from the whole ecosystem; they do not have to buy all solutions from the ecosystem. Hence the revenue model of all actors in the ecosystem will not be the same, the cooperation between system actor is a mandatory element to provide customers with what they need from the whole system. The involvement in the ecosystemic business context act as an enabler for the business organization to expand the business scope into foreign markets and ensure the transparency of the business process.

5.4 Limitations and evaluation of the research

The study objective was to increase the understanding of how to build connecting links between the big data and business model thinking in the healthcare context. The data was gathered in the form of three major case companies to formulate an overall understating of the research topic. The limitation of this research was related to the timeframe of the research, that has impacted the data collection process. Due to time limitations, the researcher did not have enough time to include more case studies and interview a wide range of industry experts. Besides, the researcher was not able to discuss in detail the points related case company's innovation strategies, hierarchal structure, and adaptability to change. It has been avoided to not impact the participants work status and enable them to present the positive aspects of their companies. To keep the anonymization of the research data, the critical information about product launching and company strategies were not revealed in this research; to keep the confidentiality and not reveal any future strategy for the selected case companies.

The selection of the qualitative research approach was the best fit for this exploratory phase of research; as it gives researchers the likelihood to examine various social phenomenon based on the viewpoint of the participants, also gain a deep understanding of the research phenomenon. A similar qualitative approach adopted in a wide range of prior studies, that were conducted to examine the value creation in data-intensive systems and identify the business models in the digital settings. The findings of this study are not generalizable due to the sample size, as this study was conducted over a small sample size including three case companies operating in the Finnish healthcare industry (Schofield, 2002).

The evaluation of this study is done through the reliability and validity measures. Hence the reliability of the qualitative research study refers to the replicability and repeatability of the research results/process (Leung, 2015). Golafshani (2003), defined reliability in terms of consistency of the research results over time. From this aspect, researchers should be able to produce similar types of research over time and reach similar findings. Considering this study, it is possible to repeatedly produce the same kind of research, because the researcher builds his researcher process to understand how to link the big data and business models in the healthcare system. The data collection and analysis method were discussed earlier in chapter 3. The empirical findings were presented in chapter 4 and 5.

The validity in the qualitative research relates to the methodology of the research and the appropriateness of the tools used to collect and analyze the data (Leung, 2015). Further, it is about the matching between the research question and the methodology of research; as the methodology should be appropriate enough to answer the research question. As the qualitative research does not have any value to measure; rather it examines and deals with the non-numerical data like case studies, depth interviews, surveys, and observations. And then, formulating in-depth knowledge in the area of research (Chesebro & Borisoff, 2007). In this exploratory research, the case study methodology was applied to enable the researcher to understand how to link the big data and business model. To approach this; the data was collected through semi-structured interviews with industry experts in the corresponding field. The collection and analysis of the empirical data were discussed in chapter 3 and 4 respectively.

Another approach defined by Altheide and Johnson (1994) to evaluate the validity of the qualitative research; as it is divided into an internal validity and external validity. The internal validity refers to the credibility and of the research; that is dependent on the quality of the research data and the participants should believe in the credibility of the research findings. In this research, we selected the participants based on their position in the companies that is related to creating new platforms for integrated solutions. External validity refers to the transferability of the research findings. It means that research results can be transferred by the readers to any other context. The findings of this study can be transferred to any other data-intensive contexts, it can be generalized an applied to other similar settings/solutions. Additionally, the confirmability of the qualitative research measures to which extent the findings of the study are supported by actual data examined by other researchers. Referring to this study, similar qualitative approaches have been applied when examining the process of value creation and business models in the data-oriented systems.

Overall, based on the reliability and validity measures defined by Leung (2015), Golafshani (2003) and Altheide and Johnson (1994); the empirical study of this research meets the requirements of the validity and reliability to an acceptable level. Further, the study considered the ethical element while formulating the theoretical background part represented in including the appropriate citation to the existing literature. While in the empirical study part, the study followed the guidelines of the abductive thematic analysis. Including the theoretical framework as a guideline for the empirical study to progress and identify the research outcomes. The data about case companies future strategies and the interviewee identity have not been revealed to ensure the security and anonymization of the data. Accordingly, this study can be considered to provide comprehensive and novel literature towards the platforms for big data business models in the healthcare context. Further, it can be used as a hypothesis for future research to test the modularity of the big data business models.

5.5 Recommendations for future research

This study suggests a framework for the big data business model in the healthcare system. It focuses on the value creation in the big data systems from various aspects related to the ownership of the big data platforms, control of the data system and ecosystemic business context. However, it is an exploratory research study that has not been applied yet in the real business environment. From this perspective, it would be interesting if the findings of this study are applied to adjust the setting of the data-oriented ecosystemic platform.

In this study, we reported the benefits and challenges that the big data business model may face; in terms of the ecosystem business containing several companies with different goals and interests. Then, this study could be as a hypothesis for future studies to test the modularity concept and determine whether the use of data could change the role of control in the big data ecosystem. Further, examining how to align different revenue models together within the same ecosystem.

Also, it would be interesting if further study tries to investigate the impact of modularity in the big data systems, and how it can help in expanding the business scope and growing to the foreign market. As this study was conducted with a focus on the Finnish healthcare system, it important to examine this concept on an international scale to identify the relationship between modularity and consistency in the business process.

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APPENDIX I

Outline for the semi-structured interviews

This study aims to develop a framework for understanding the platforms for big data business models in the healthcare context.

Background questions

1. Could you please give a brief description of your position and the main duties?
2. Could you tell a bit about what your company is doing?
3. How would you like to describe your organization and its structure?
4. What kind of innovation strategy your company is following?

Big data related questions

5. Could you please tell what big data means to you?
6. What is the role of data in your business, especially if you think about the icory project as an example?
7. What is the role of control in your business and how is it related to the efficiency and effectiveness of the business process?
8. How do you see the concept of access rather than ownership when you are looking to the efficiency of the business process?
9. Relating to the concept of access rather than ownership, what kind of conflict that might be possible? What is the possible solution strategy?
10. Do you think the sharing concept enables your customers to get cost-efficient access to the service? How does it work?
11. How do you manage the different aspects related to data when minding customer experience?

Ecosystemic business model related questions

12. How would you describe the business model of your company?
13. How is your company business model is integrated with partners business models?
14. What are the most important aspects of business relationships?
15. How do you create and deliver the value to your customer?

16. How do you cooperate with other partners to provide a superior customer experience?

Big data business model related questions

17. How do you view the centralized control over one single data source? How does it help the central repository to grant standardized access to system participants?
18. How can the centralized control bring the conflict to the business relationship and what are the possible solutions?
19. How the co-operation with other partners help your company to create and deliver value?
20. Do you use any software like SaaS as a software distribution model? If yes, what are the driven benefits for your company's business process and other trade partners? (In terms of minimizing the data transfer time and overcoming any performance gaps).
21. How these platforms (Like SaaS) help companies to strengthen their relationship?
22. What are the challenges that might come when working without partners in the business environment?
23. Relating to the innovation strategy that we have discussed earlier, what is the role of the business partnership in providing an innovative business process?
24. What are the techniques your company tries to use to achieve the consistency of the business process?
25. Referring to the corporation, sharing, and integration concepts. What are the challenges that any business organization can have from applying these concepts? What are the possible solutions for these challenges?
26. Did our discussion bring something in mind that we have not discussed yet?